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Dynamic Modeling of Household Electricity Consumption

Master's Thesis
Espoo, August 13, 2012

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ABSTRACT OF MASTER'S THESIS

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The change in household electricity consumption affects many parties in the electricity business, and therefore more accurate tools for analysing the possible outcomes are needed. In this thesis, the objective is to implement a tool capable of producing future scenarios of the electricity consumption and load profile changes using structural modeling techniques. The tool consists of two simulation models, which are integrated and can be used separately or as one.

The long-term model, describing household electricity consumption change during the next 40 years, is made using system dynamics approach. The short-term model, describing daily and weekly load profiles, is made using bottom-up approach. By dividing the problem into two models the benefits from both top-down and bottom-up approaches can be used and the problems related to stiff systems can be avoided.

The long-term model is validated against historical data and with expert evaluations. The model can be used for generating scenarios of the future household electricity consumption and the user can change parameters by using the implemented user interface.

Integration of the two different approaches was successful and the model is able to address how different changes in the long-term model, such as the number and energy efficiency of appliances, are affecting the load profiles. However, the short-term model is incomplete and therefore the simulation results are only indicative.

Keywords:	Electricity consumption, dynamic systems, system dynamics, load profile, smart grid, demand-side management, demand response, consumer behavior, households, tariff structures
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Kotitalouksien sähkönkulutuksen kehitys vaikuttaa eri osapuoliin sähkömarkkinoilla, jonka takia sähkönkulutuksen tarkempi analysointi on tarpeellista. Tarkoitus on tehdä simulointityökalu, jolla on mahdollista testata erilaisia skenaarioita kotitalouksien kokonaissähkönkulutuksen ja kuormituskäyrien kehityksestä. Työssä on käytetty rakenteellisia mallinnusmenetelmiä. Työkalussa kaksi eri simulointimallia on integroitu yhdeksi kokonaisuudeksi. Malleja voidaan käyttää yhdessä tai erikseen.

Pitkän aikavälin malli, joka tarkastelee kotitalouksien sähkönkulutuksen muutosta seuraavan 40 vuoden aikana, on tehty käyttäen systeemidynaamista mallinnusmenetelmää. Lyhyen aikavälin malli, joka kuvaa päivä- ja viikkokuormitusprofiileja, on tehty bottom-up -ajattelun pohjalta.

Pitkän aikavälin malli on validoitu historiadataa vasten sekä asiantuntija-arvioilla. Malli pystyy tuottamaan skenaarioita kotitalouksien sähkönkulutuksen kehityksestä; käyttäjä voi halutessaan muuttaa mallin parametreja käyttöliittymän avulla.

Kahden eri mallinnusmenetelmän integrointi onnistui hyvin ja mallilla voi testata kuinka muutokset pitkän aikavälin mallissa, kuten kotitalouslaitteiden määrä ja energiatehokkuus, vaikuttavat kuormitusprofiileihin. Lyhyen aikavälin malli ei kuitenkaan ole vielä valmis, joten simulointituloksia voi pitää pelkästään suuntaa antavina.

Asiasanat:	Sähkönkulutus, dynaamiset systeemit, systeemidynamiikka, kuormituskäyrä, älykkäät sähköverkot, kuluttajakäyttäytyminen, kysyntäjousto, kysynnänohjaus, tariffirakenteet
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Espoo, August 13, 2012

Tomi Sorasalmi

Abbreviations and Acronyms

Abbreviations

AMR	Automatic Meter Reading
BAU	Business-as-usual scenario
CET	Central European Time
CPP	Critical Peak Pricing
DR	Demand Response
DSM	Demand-side Management
EU	European Union
GDP	Gross Domestic Product
GSHP	Ground Source Heat Pump
HEV	Hybrid and Electric Vehicle
HVAC	Heat, Ventilation, and Air Conditioning
LED	Light-Emitting Diode
RTP	Real-time Pricing
ToU	Time-of-Use
TSO	Transmission System Operator
VBA	Visual Basic for Applications
VTT	VTT Technical Research Centre of Finland

Terminology

Distributor	Transfers the electricity from the main grid to the end-user. Owner of the transmission net.
Load Profile	A graph describing the variations in the electrical load versus time.
Producer	Generates electricity in the power plants.
Scenario	A possible future path of development.
Smart meter	Measures electricity consumption in a given time interval and delivers information for monitoring and billing purposes.
Spot/System Price	Electricity price for a given time interval, typically for one hour.
Supplier	Buys electricity from Nord Pool and sells it to the end-users.
TSO	Transmission System Operator. Is responsible of the main grid. In Finland the TSO is Fingrid.

Contents

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Chapter 1

Introduction

This chapter contains the introduction of the thesis. Section 1.1 presents the background, Section 1.2 clarifies the research objectives, and Section 1.3 presents the structure of the thesis.

1.1 Background

Electricity consumption is changing over time and affecting more or less the whole society. For many actors in the electricity business, especially producers and distributors, knowing the future consumption would be a great advantage, and therefore the ability to produce reliable scenarios of the future consumption is important.

Household electricity consumption constitutes roughly a quarter of the total consumption of Finland. However, in some residential areas the proportion is much larger. Industrial electricity demand is relatively steady whereas household consumption is dependent on the time of the day, i.e. low during the night and high in the morning, late in the afternoon, and in the evening, therefore having a large impact on the daily load profiles.

This thesis addresses how dynamic modeling can help generate scenarios of future electricity consumption and load profiles. Electricity producers, suppliers, and distributors require knowledge of the total consumption to support their businesses, e.g. new capacity investment decisions. Production plant and electrical grid investment projects can take more than a decade from the investment decision to the project conclusion, which creates stringent requirements for more accurate scenario tools.

The main purpose of this Master's Thesis is to study changes in household electricity consumption. Two separate simulation tools are introduced to describe long- and short-term behaviour. The long-term model is created using system dynamics approach; the model is done with Vensim-software. The short-term model is created using Apros-software and Microsoft Excel -program. Also, an integrated model of these two separate models is introduced, which can be used to simulate the evolution of the total consumption and hourly load profiles over the next decades.

The scenario analysis tool allows the user to test different scenarios, such as technological development, structural changes in housing, introduction of energy saving laws, changes in long-term consumer behaviour, hybrid and electric vehicle breakthrough, passive house breakthrough, and lighting technology development (i.e. LED). The model could also be developed to support electricity tariff testing, but this is left for further research.

System dynamics enables new ways to solve problems and understand entities in the complex and evolving world. The purpose is to support decision-makers to operate in this complex environment. The approach offers an alternative way to solve and more deeply understand traditional problems. Modeling offers means to study the structure of the underlying system and to test different scenarios. The underlying assumption is that the structure determines the behavior. Also a large amount of variables, which affect the behavior, can be taken into consideration. Simulation facilitates testing different assumptions and their causes. [1] [2]

1.2 Research Objectives

The objective of this thesis is to model the evolution of long-term electricity demand, especially household electricity consumption. The electricity consumption is changing due to different reasons, e.g. growth in population, dwelling stock, appliance stock, and increase in energy efficiency. The purpose is to understand why and how this change is taking place. The structure of the system, feedback loops and delays are determining the behavior, and therefore a dynamic approach is required. A scenario analysis tool is created to test how the electricity demand is likely to evolve in the future and to give insight which parts of the system are the most important.

Another research objective is to present a method to model the evolution of electricity load profiles over time, since this is an important problem not yet solved.

1.3 Structure of the Thesis

Following the introduction this thesis has eight chapters, which are organized as follows: in Chapter 2 the background of electricity markets is presented. In Chapter 3 system dynamics is presented. In Chapter 4 household consumption habits are discussed. In Chapter 5 the created system dynamics model is presented. The model describes the long-term change in household energy and electricity consumption. In Chapter 6 the Apros-model is presented, which describes the short-term electricity consumption, especially load profiles. In Chapter 7 the integrated model of system dynamics and Apros is presented. In Chapter 8 the conclusion is presented and future research topics discussed.

In this thesis, two models are formed, a long-term model and a short-term model. Here the differences between these two models are addressed to clarify the structure of the thesis: The long-term model (top-down approach using system dynamics) is presented in Chapter 5. The short-term model (bottom-up approach) is presented in Chapter 6. In Chapter 7 these two models are integrated and the advantages of the integration are presented.

Chapter 2

Electricity Markets

Modern societies require reliable and safe energy and electricity production. Finland is accustomed to cheap electricity prices on EU level during the past years [3]. Nordic countries have huge water resources harnessed for hydroelectric power, large amount of nuclear power, and a well working electricity market. Cheap electricity is not the only special energy characteristics of Finland. Most of the world is more concerned of cooling whereas Nordic countries use most of the energy for heating, and therefore electricity is cheap in summer and in flooding times and expensive during cold winter months of high consumption.

A well functioning electricity market and supply are very important for ensuring societies to function smoothly. Every now and then there are blackouts in the electrical grid leading to significant losses in economy, although Finland has avoided large blackouts so far. This is also a matter of safety, as several crucial functions need to work at all times or people might be in danger; hospitals and traffic lights, for instance, need to function without stoppages. National and cross-national electricity markets, such as Nord Pool, are designed to provide a reliable supply of electricity for all parties at all times.

This chapter presents the structures of electricity markets and Nord Pool. Section 2.1 gives a general overview on electricity markets. Section 2.2 explains the structures of Nord Pool. Section 2.3 takes a closer look at the future of Nord Pool and electricity market innovations.

2.1 Introduction

In Finland the electricity market has changed over the last 17 years remarkably. In the year 1995 the reformation of the electricity markets started leading to deregulation and opening the markets for free competition. At the beginning of the reformation only large consumers were able to bid their electricity contracts freely, but now also small customers can bid their electricity contracts. [4]

Electricity markets differ from other bulk markets because of the non-storability of electricity. Electricity has to be produced at the same time it is consumed, in other words real-time supply and demand has to be in balance at every time instant. This combined to the situation of almost non-existent elasticity on demand is a great challenge for electricity markets in general. [5]

Electricity markets consist of different actors who have different interests. The main players in the electricity markets are producers, distributors, suppliers, transmission system operators and customers.

In an efficient electricity market, demand and supply determine the spot price. Nord Pool is a good example of such an electricity market. Nord Pool is also an excellent example of a deregulated cross-national electricity market; the relatively fast development of a smart grid makes it even more interesting. Nord Pool has been a forerunner of modern electricity markets, and it is the largest functioning multinational electricity market including Finland, Sweden, Norway, and Denmark. Cooperation widens all the time, currently including Estonia, Germany, and Great-Britain. [6] [5] [7] [8]

In a deregulated market supply, demand, and possible constraints, such as transmission capacity, determine the electricity price. In a regulated market authorities determine the electricity price. Despite the benefits of a free market most of the world's electricity markets are still regulated. Nord Pool has deregulated electricity production and supply, but regulated electricity transfer. [6]

In many countries, also in the EU, the deregulation of electricity markets is moving fast because multiple benefits can be gained by freeing electricity markets to free competition. A deregulated market usually works more efficiently because of better optimization of supply and demand, which leads to more reliable supply by securing a reasonable price for producers, and by decreasing peak demand. The larger the electricity market the better it can balance the supply and demand. In a larger geographical area supply and demand peaks can be more effortlessly compensated, leading to a more effective capacity utilization [6].

Deregulation has many advantages, however, deregulated electricity markets can suffer from boom and bust cycles, as many other commodity and bulk markets. [9] [10]

Amundsen *et al.* [11] state in their paper that Nord Pool has worked well because it has been built to be simple and effective; no one has too much power in the market and Nord Pool has a strong political support. This does, however, not mean that Nord Pool could not be developed further.

The electricity price in Finland is determined by multiple factors; demand, supply, and transfer capacity. Also such factors as the amount of water in the pools of hydro power plants in Sweden and Norway affect the electricity price in Finland. Figure 2.1 presents how much the electricity price can change in one day. A 5-day period, from 28th of September until the 2nd of October in 2011, was relatively warm in Finland, and in Sweden and Norway the water reservoirs were full. Together this resulted in all-time low electricity prices in Finland. On the other hand the long-term price is affected more by the total electricity production capacity and total demand development. Relatively small changes in electricity demand can result in quite large variation in the electricity price.

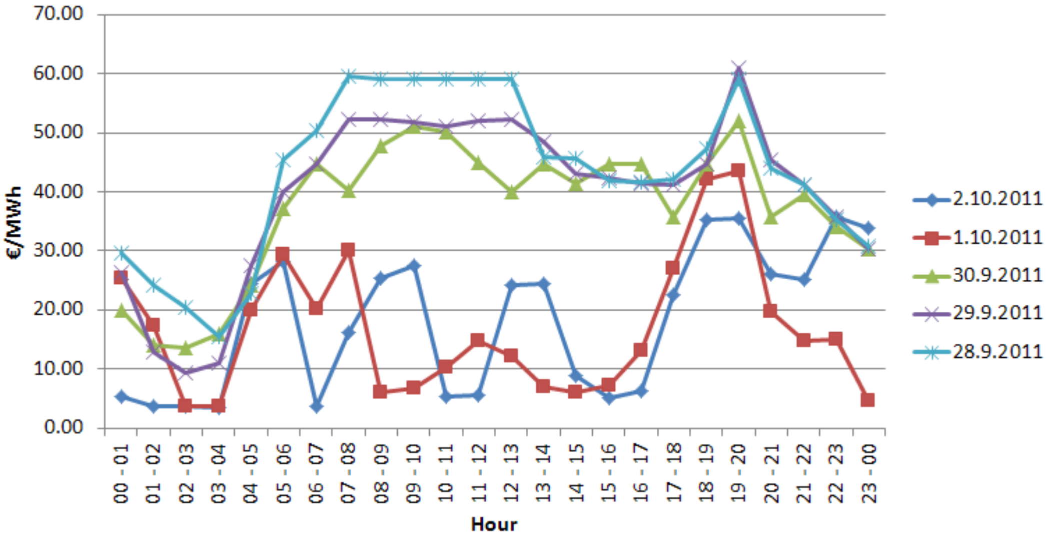


Figure 2.1: Hourly electricity prices, 28.9. - 2.10.2011 [6]

Figure 2.2 presents daily load profiles, electricity demand hour by hour, from the 28th of September until the 2nd of October in 2011. These volumes can be compared to the prices shown in Figure 2.1, since the time period is the same. Electricity demand is the lowest during the night, and in the morning, when people wake up, the consumption increases. In the morning, a peak might occur. During the day, when people are at work, the consumption is less volatile. Demand peaks can occur again in the evening, when people come back to home after work.

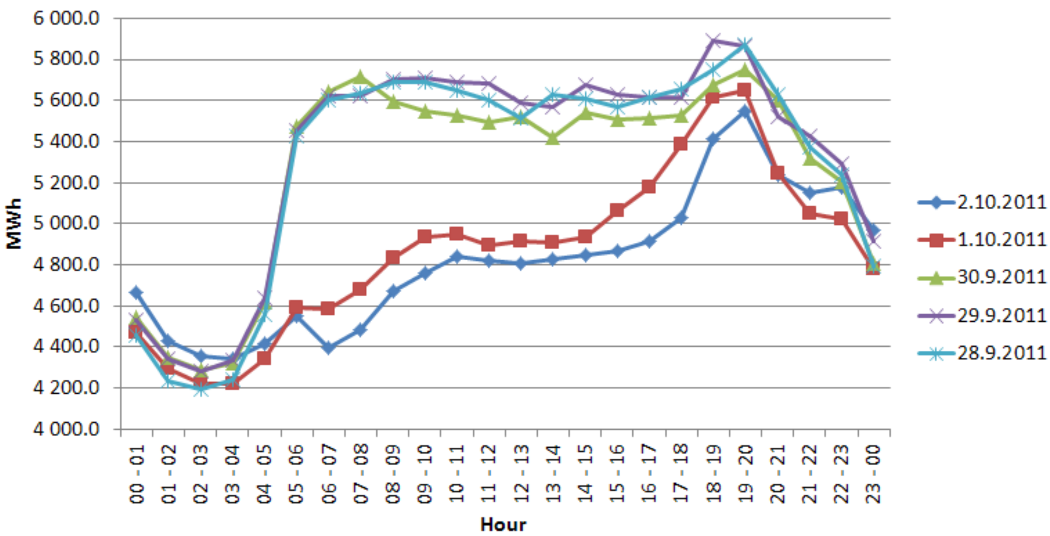


Figure 2.2: Hourly electricity volumes - load profiles, 28.9. - 2.10.2011 [6]

Figure 2.3 presents monthly electricity price development in Finland in 1999 - 2011. The long-term electricity price has been increasing steadily, and price peaks have occurred more regularly in the last few years than the beginning of the decade. Figure 2.3 also reveals that electricity is cheap in the summer and expensive in the winter.

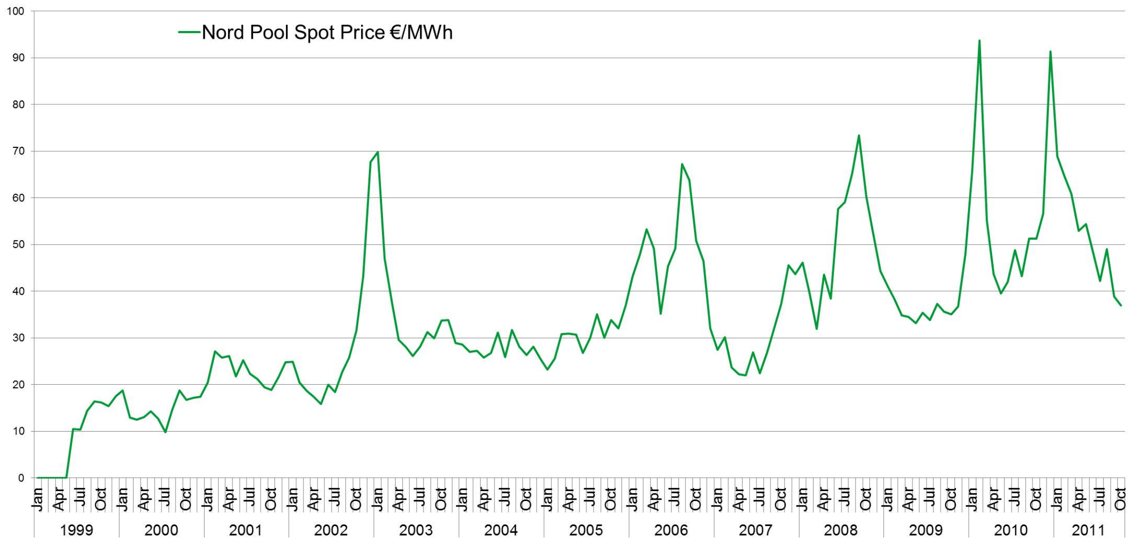


Figure 2.3: Monthly electricity prices in Finland, 1999-2011 [6]

2.2 Nord Pool

This section presents the Nordic electricity market, Nord Pool, in more detail. Nord Pool is the world's first functional multinational electricity market. It was established in 1996, and currently it is also one of the largest of such kind. Nordic countries have been in the forefront of deregulating electricity markets; Norway was one of the first countries in the world to do so in the early 90's, and Finland, Sweden and Denmark followed soon after. This finally led to a common electricity market in the Nordic countries. Nowadays already 74 % of all the electricity consumed in Nordic countries is traded in Nord Pool. During the year 2010 the total amount of electricity traded in Nord Pool was 310 TWh, in euro it sums up to 18 billion euro. [6]

Nord Pool consists of different market systems: day-ahead, intraday, and financial. The most important is the day-ahead market, where most of the trading, which considers next day electricity, is done. The intraday market trading, on the other hand, is in essence real-time. It is used to smooth production shortages that are impossible to accommodate beforehand. The financial market (Nasdaq OMX Commodities) is for longer-term electricity trading, the time scale being from one day up to six years. [6]

In Finland the industry is consuming approximately 55% of electricity. There are approximately 3.2 million small electricity users, namely households. Households consume approximately 22% of electricity. During the coldest winter days, peak demand can be up to 15 000 MW. [6]

2.2.1 Market Participants in Nord Pool

There are different participants in Nord Pool, as already mentioned earlier. The main participants are producers, distributors, suppliers, and transmission system operators (TSO). There are also many other participants operating in the market, e.g. brokers, clearing companies, and financial analysts. If the electricity market is regulated, then often all these participants have a monopoly in their area and some official party decides the electricity price. Nord Pool is a partly deregulated market, meaning that producers and suppliers operate under free competition, but TSOs and distributors have a monopolistic position. [6]

At the moment there are more than 350 producers, approximately 500 distributors, approximately 350 suppliers, and added to that all traders and brokers and other market participants. In the same geographical area there are approximately 14 million end-users. This all makes Nord Pool the world's largest electricity market. [6]

Producers are companies that produce the electricity in their power plants. Electricity production is under free competition and all producers have the same rights to sell electricity on Nord Pool or directly to the major electricity consumers. Also the TSO and distributors have to treat all of the electricity producers equally. The largest producers in Nord Pool are Fortum, Vattenfall and Statkraft, which have approximately 50% of the market share. [6]

Suppliers are companies which buy electricity from Nord Pool and sell it to the end-users. Electricity supply is deregulated. This means that a supplier can sell electricity to any customer inside the country it is operating in. In other words consumers can freely select from which supplier they purchase their electricity. Electricity distributors are obligated to transfer electricity with the same conditions for all suppliers. Suppliers have to be separated from distributors, they cannot be the same company, although many suppliers and distributors are operating under the same name. The largest suppliers are Fortum, Vattenfall and Dong Energy, which have approximate 25% of the market share. [6]

Distributors are companies which transfer the electricity from the main grid to the end-user, using the transmission net. Distributors are not selling electricity, they are only transferring the electricity that someone else has sold. Distributors have monopolies in their area, yet they have to treat all electricity suppliers equally. The government is regulating the distributors and determining the electricity transfer price. The distributor of a certain area is responsible for the development and maintenance of the network in that area [12]. The largest distributors in Nord Pool are Fortum, Vattenfall and E.ON, which have a total market share of approximately 25% [6].

A TSO's function is to provide electricity transmission in the main grid. In Finland the TSO is Fingrid. Fingrid's largest owner is the Government of Finland. Electricity producers are no longer allowed to own Fingrid. TSOs are obliged to treat all market participants equally and transfer electricity with the same conditions to everyone. [13]

A typical household consumer purchases electricity from a supplier. A distributor delivers the electricity since the distributor owns the local transmission grid. The consumer pays the transmission costs and the electricity taxes to the distributor. A TSO makes sure that the distributor has enough electricity available from the main grid. The supplier purchases electricity from Nord Pool and pays the system price. The supplier charges the consumer for the electricity price plus a suitable margin. Nord Pool fixes the price based on demand and supply. Producers produce electricity based on the price. [6] [12]

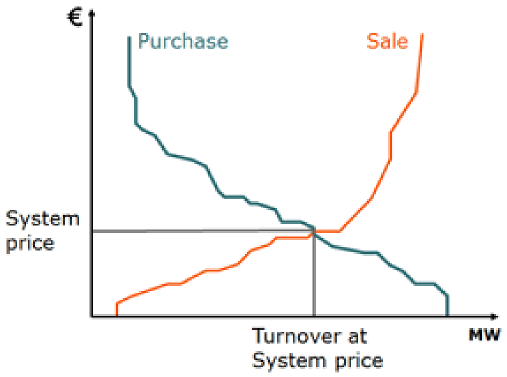
At the moment the electricity price for household customers is the sum of three parts; the electricity price, transfer price, and taxes. Respectively each of them covers roughly one third of the electricity bill. As mentioned earlier, the consumer can tender suppliers, but not distributors.

2.2.2 Day-ahead Market - Elspot

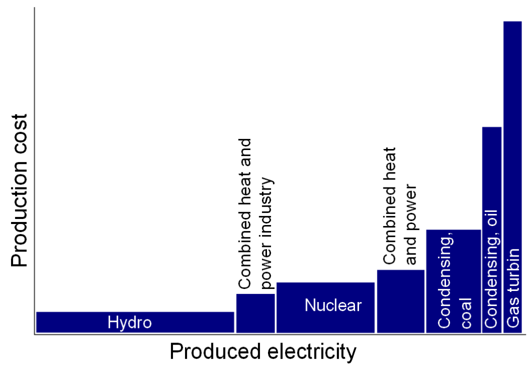
The main market for trading electricity in Nord Pool is the day-ahead market, Elspot. Sellers and buyers leave their bids and the hourly price is set by supply and demand. The Elspot trading system plays an important role, as the seller and buyer are setting their bids on this system. The bids contain information on how much electricity and for what price they are willing to buy or sell. 12.00 CET is set as a deadline for the next days electricity bids. Based on the bids, Elspot's algorithm calculates prices for every hour of the following day. Basically the electricity price is determined by the intersection of demand and supply curves, as seen in Figure 2.4a. The intersection determines the system price at which electricity is sold and the turnover of how much is sold. This system price will be adjusted if there are any constraints in the transmission capacity. [6]

A transmission constraint refers to a situation where the transmission capacity cannot deliver enough electricity from area A to area B. Because of the transmission constraints, area prices are also needed. Finland and Sweden, for instance, might have a different electricity price if there is not enough transmission capacity to transfer the electricity from the surplus to the deficit area. Area prices are designed to decrease demand in areas where transmission constraints are limiting electricity supply and increase the demand in surplus areas. [6]

As can be seen in Figure 2.4b, the price of electricity production varies greatly depending on the production method used.



(a) Price mechanism, supply and demand [6]



(b) Production costs of different production methods

Figure 2.4: Price mechanism and production costs of different production methods.

2.2.3 Intraday Market - Elbas

It is impossible to effectively store electricity, and this differenciates electricity markets from other commodity markets. This generates restrictions, for instance supply and demand have always to be in balance. The day-ahead market does most of the balancing work, but the intraday market, Elbas, has also an important role. [6]

The Elbas is designed to do what the day-ahead market cannot do, that is real-time adjustments to electricity prices due to production shortages, or for example because the electricity produced by wind power is hard to predict on the previous day. Elbas covers the Nordic countries, Germany and Estonia. Elbas trading takes place at the latest one hour before the delivery. Currently most of the electricity is traded in the day-ahead market, but the intraday market is becoming more and more important as more wind power is built. [6]

2.2.4 Financial Market, Nasdaq OMX Commodities

In Nord Pool financial contracts, long-term electricity trading is done in the Nasdaq OMX Commodities market. The time scale is from one day up to six years. Financial market uses the day-ahead market prices as the reference prices. Different parties in Nord Pool are using financial contracts for risk management and to secure their electricity demand or supply at a certain price. In the Financial market physical electricity is not traded, only derivatives. [6]

2.3 Nord Pool Evolution and Smart Grid

Nord Pool is still quite a young system and it is under constant change. According to Nord Pool Spot [6] the Nordic electricity market, Nord Pool, will continue its expansion. The grid has already connections to Baltic countries, Germany and Great Britain. There are also other interesting changes pending, for instance, the introduction of smart grid. Hybrid and electric vehicles are also interesting because of the possible rapid increase in electricity consumption in the coming years [14].

2.3.1 Smart Grid

A smart grid refers to an electricity transmission system, which is capable of better collecting and delivering information and operating based on this information. A smart grid consists of an existing electrical grid, automation, information, and communications technologies. This all constitutes a joint entity which is called a smart grid. Besides ICT systems smart grid requires Automatic Meter Reading (AMR) technology, e.g. smart meters. Smart meters are connecting end-users to the smart grid enabling the utilization of smart grid applications. [15]

Benefits of a smart grid include a more reliable grid and more efficient capacity utilization. The condition of an electrical grid can be also more easily monitored and it is faster to respond to malfunctions. [15]

Currently, electricity meters are measured once a year when electricity company representatives read the meters manually. Electricity invoicing is based on a monthly estimate and yearly compensation. A smart meter enables real-time consumption monitoring. The objective is to have smart meters installed in 80% of the households at the end of the year 2013 [16].

Koponen *et al.* [17] report that the benefits of smart meters are remarkable. As mentioned above, electricity reading will be real-time. For consumers, this enables real-time consumption monitoring, and therefore demand response and price elasticity. For electricity suppliers, this enables easier and more accurate invoicing, easier meter reading, and better customer service. Smart meters also enables using automatic control systems, which can help to save energy. [17]

There are also many other topics related to smart grids. Smart grid, for instance, enables decentralized electricity production where also consumers can be producers and sell electricity to the main grid. Especially renewable energy sources, e.g. wind power, creates new kind of challenges to the electrical grid and electricity markets. The amount of small power plants, e.g. wind and solar energy, is increasing all the time. Households as producers is already present-day technology in Germany and at some point this will be the state-of-the-art technology also in Finland. Because of the decentralization also the importance of demand side management will increase; the production will not stay as steady as it has been. [18]

For instance, merely a hybrid and electric vehicle (HEV) propagation sets challenges to the electrical grid. Ruska *et al.* [14] state that if HEVs propagate rapidly, in the year 2020 they consume approximately 0.6TWh electricity, and this corresponds to 200 000 HEVs. In the year 2030 the same scenario predicts 1.23 million HEVs and 3.9 TWh consumption. Ruska *et al.* claim that unoptimized charging of HEVs will increase the demand peaks of the late afternoon and evening, thus worsening the load profiles. In the best case successful optimization of HEV charging would flatten the load profiles. [14]

Smart grid is important when considering the breakthrough of HEVs and the challenges this brings. Failing to organize the charging of HEVs means problems in the electrical grid, which inevitably has consequences to the propagation of HEVs.

For further information about the current status of smart grid in Europe, see Giordano's [8] list of Smart Grid projects in Europe.

2.3.2 Tariff Structures

The most common tariff structures, presented in Figure 2.5, are constant price, Time-of-Use (ToU), Critical peak pricing (CPP), and Real-time pricing (RTP). Suppliers are using different tariffs for different customers. The most usual is a constant price. ToU-pricing is also common, this means that suppliers are selling day/night, week/weekend, and summer/winter tariffs. It is also possible to use a system price tariff that is following the system price although for the time being it is usually a monthly average, but soon it might be the real system price due to automatic meter reading. [19] The benefits and possible consequences of new tariff structures are discussed more in Chapter 4, Section 4.4.

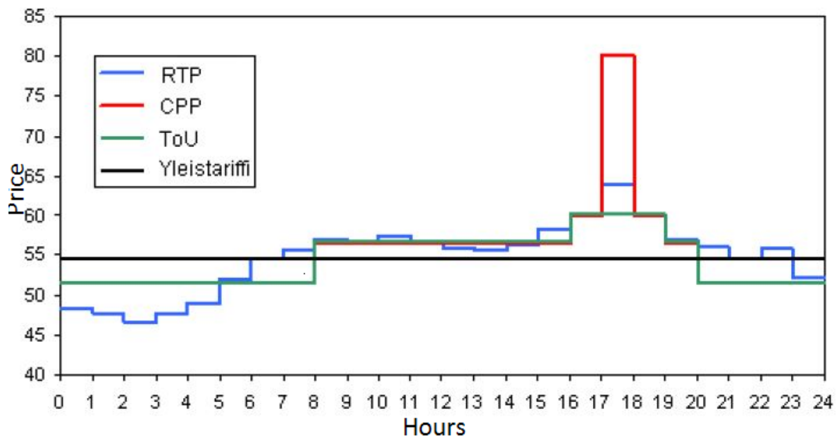


Figure 2.5: Different tariff structures. From top: RTP, CPP, ToU, and constant price (constant price states as "yleistariffi" in the figure). [20]

Chapter 3

System Dynamics

Systems engineering is used in many ways to help designing and understanding better systems. One application area is to overcome the limitations of human mind when dealing with complex systems. Systems engineering methods (e.g. system dynamics) apply engineering, especially mathematics, systems theory, and control theory, to technical and non-technical problems.

System dynamics is a tool combining systems thinking and mathemathical modeling, which together can help decision makers to evaluate and understand the problems. The underlying assumption is that the structure is more important determining the behavior than the actions of the individual actors.

This chapter clarifies the concepts of system dynamics. Section 3.1 introduces ideas about system dynamics including a brief history. Section 3.2 explains the concept of causal loops. Section 3.3 explains briefly the basic building blocks of system dynamics, i.e. stocks and flows. Section 3.4 explains the basic properties of dynamic systems. Section 3.5 explains the basic dynamic modes of dynamic systems. Section 3.6 presents an overall view to models and modeling. Section 3.7 gives a short literature review on the applications of system dynamics used in energy markets.

3.1 Introduction

Real world systems are in many cases too complex for human brains to analyse. Dynamic complexity can arise from feedback loops, delays, and nonlinearities. Ford [21] states that humans are not able to see the outcomes of their actions, especially when operating in a dynamic world, where long delays occur between the actions and the consequences.

System dynamics is originally developed by professor Jay W. Forrester from MIT in the 1950s. He applied system dynamics to industry production chain management and other industrial systems. The main idea was to model organization structures using stock and flow diagrams. In the coming years, Forrester applied system dynamics to economics, social science, and urban planning. System dynamics approach spread rapidly from the original industrial applications to many other disciplines making complex dynamic systems easier to understand. [22] [23]

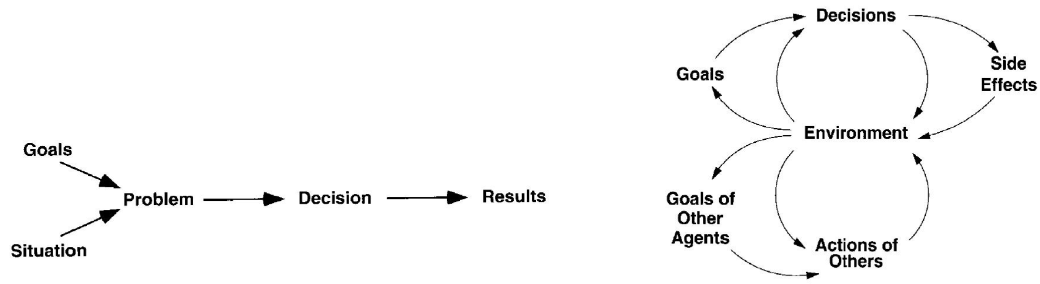
Today system dynamics is applied to different problems in many fields, such as supply chain management [23], climate change [24], and business systems [1].

A system is a set of parts interconnected to form a structure that produces a certain behavior. A dynamic system is a system which has memory, meaning that the previous states affect the future states. System dynamics is a way to study the structure and behavior of complex systems, and therefore the main objective is to describe the structure as truthful as possible using causalities, feedback loops, delays, and nonlinearities. This all creates a complex and nonlinear model, which is difficult to understand. Therefore the behavior is usually studied by computer simulations. Computer modeling and simulation makes system dynamics especially effective and powerful. [25] [21] [1]

System dynamics is above all based on the assumption that the behavior, sometimes undesirable and uncontrollable, is a result of the system's structure. Therefore the structure should be studied rather than the behavior itself. It is important to understand the behavior of the system as a whole, because different parts are interacting inextricably with each other. This part of the process is usually called systems thinking, which includes determining causalities, feedback loops, and model boundaries. When there is an understanding about the structure and possible behavior modes, a mathematical model (system dynamics) describing the system can be built.

System behavior cannot be explained comprehensively by only by studying the behavior of different parts of the system. Interactions between the parts play a crucial role in determining the behavior of the whole system. The interactions between model parts and variables are described by mathematical dependencies. [1, pp.107-133]

In some modeling techniques, the feedback loops are left outside the research and systems are examined with simple open loop diagrams, as seen in Figure 3.1a. Another common shortcoming is to take into consideration only the most important part at the expense of forgetting the less obvious reasons. However, these less obvious reasons might have a substantial effect on the whole system; especially the long-term effects might remain undetected. It is also common to neglect the consequences of one's own actions or just resort simplifying too much. In system dynamics simplifying too much is avoided and one's own actions are taken into consideration. Figure 3.1b presents how decisions affects the environment, also other actors and side effects are taken into the model. [1, pp.3-12]



(a) Open loop -diagram (b) Closed loop -diagram

Figure 3.1: Cause and effect diagrams: traditional and system dynamics perspective. Traditional approach concentrates on one's own actions, while system dynamics approach includes also the side effects and actions of others. [1, p.10-11]

The concept of endogenous change is an important part of system dynamics, and therefore problems are usually seen as endogenous; this is why the solution has to be endogenous too. To solve the problem, the source of the behavior, the structure, has to be revealed. [26]

3.2 Causal Loop Diagrams

In this section, a common system dynamics way of presenting dynamic structures and causalities is presented. Figure 3.2 presents a reinforcing (positive) feedback loop and a balancing (negative) feedback loop. Arrows illustrate the direction of the cause and information. Plus and minus signs illustrate the polarity of the effect. A plus sign means that if A increases then B increases (if A decreases then B decreases). A minus sign means that if F increases then D decreases (if F decreases then D increases). To summarize: in causal loop diagrams (+)-sign denotes change in the same direction and (-)-sign change in the opposite direction. Different modelers use different symbols in the models. A reinforcing loop can be indicated with the letter R, (+)-sign, or avalanche sign and a balancing loop with the letter B, (-)-sign, or seesaw sign. [1, pp.137-141]

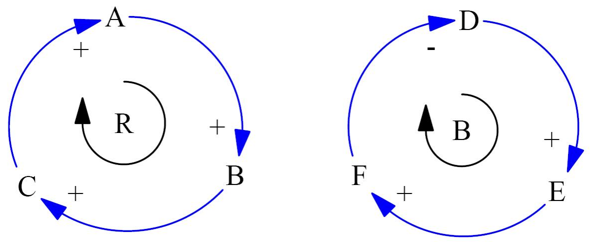


Figure 3.2: Reinforcing and balancing loops

Causal loop diagrams with feedback loops and causalities give a clear description of the cause and effect relations, and therefore they are a powerful way to conceptualize the structure of a complex system. This is a useful way to communicate and discuss the models also with people with no background in system dynamics and computer modeling. [26] [1, pp.137-141]

3.3 Stocks and Flows

Stocks and flows are essential building blocks when modeling dynamic systems. Stocks represent integrators, the state of the system, thus giving memory and inertia to the model. Flows change the state of the stocks. In Figure 3.3 stock and flow symbols are illustrated. Eqs. (3.1) and (3.2) illustrate the same mathematically. [1, pp.191-229]

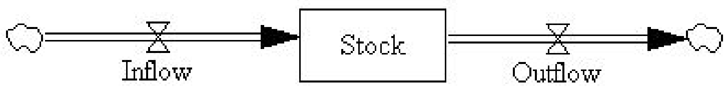


Figure 3.3: Stocks and flows

$$Stock(t) = Stock(t_0) + \int_{t_0}^{t} [Inflow(\tau) - Outflow(\tau)]d\tau \tag{3.1}$$

$$\frac{d}{dt}Stock(t) = Inflow(t) - Outflow(t) \tag{3.2}$$

3.4 Properties of Dynamic Systems

In this section the properties of dynamic systems are illustrated. Feedback loops, delays, and nonlinearities give rise to complex behavior.

3.4.1 Feedback Loops

Feedback loops are an important part of the system and they enable complex behavior. There are only two different feedback loops, a positive and a negative, as already seen in Figure 3.2. A positive feedback loop denotes a reinforcing loop. A negative feedback loop denotes a balancing loop. Systems might consist of hundreds of feedback loops. [1, p.14]

3.4.2 Delays

Sterman [1, p.411] defines a delay as a system that takes an input and gives an output that lags behind the input. Delays are important in dynamic systems; a delay in a negative feedback loop is usually the reason for overshoot and oscillation.

However, delays are not always bad, they can also filter unwanted noise and give a clear sight of the signal.

Figure 3.4 presents how delays affect the output when the input is a unit pulse at time zero. The curves A, B, C, and D describe the probability distribution of how long it takes for an item to exit the delay, in all cases the average delay time is the same. Outflow A denotes a pipe delay (infinite order delay) where all items exit the delay exactly after the time delay. Outflow B denotes a first order delay, where the items first enter a stock and then they can exit the delay. Outflows C and D denote higher order delays, where items have to enter several stocks before exiting the delay.

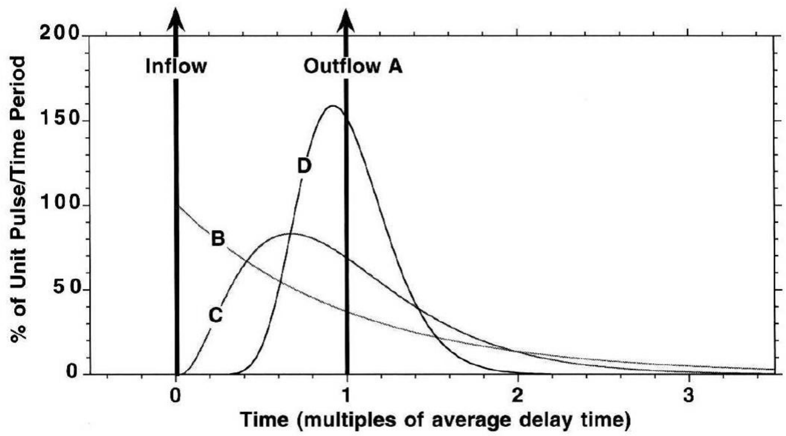


Figure 3.4: The effect of delays to the output when the input is a unit pulse at time zero. [1, s.413]

3.4.3 Nonlinearities and Loop Dominance

Sterman [1, p.551] states that nonlinearities are fundamental properties in systems of all kind. This has been known for centuries, but only recently the fast development of computer simulations has given recourses to study and incorporate these relationships effectively in dynamic modeling.

Often the complex behavior is caused by nonlinear relationships, which enable change in loop dominance depending on the state of the system. In s-shaped growth, for instance, first an exponential growth is taking place caused by a positive feedback loop. At some point the loop dominance is shifted to the negative feedback loop thus resulting in a goal seeking behavior. This is an endogenous property of nonlinear dynamic systems. The ability of nonlinear dependencies to generate shifts in loop dominance is an important reason for the use of nonlinear modeling. [26]

Nonlinear relationships enable also many kind of behaviors that are not possible in linear systems, such as multiple equilibriums, bifurcations, limit cycles, and chaos. [27, pp.1-14]

3.4.4 Dynamic Complexity

Complexity is often understood as a large amount of components in a system or as a large amount of decisions that can be made, and therefore finding an optimal decision out of a vast amount of possible decisions is called a complex problem. [1]

There are also other kinds of complexity, i.e. dynamic complexity. Dynamic complexity does not need a large amount of parts interacting together, it can arise from very simple situations. The behavior of a simple system with feedback loops, delays, and nonlinearities can be very complex indeed. [1]

In dynamic systems today's actions might be tomorrow's problems, the system is in constant change, and there might not be an equilibrium the system is converging to. Dynamic complexity arises over time and because of the time it is difficult to understand. [1, p.21]

Real world systems can be complex due to large amount of components and due to dynamic relationships. In system dynamics modeling both sources of complexity are taken into account.

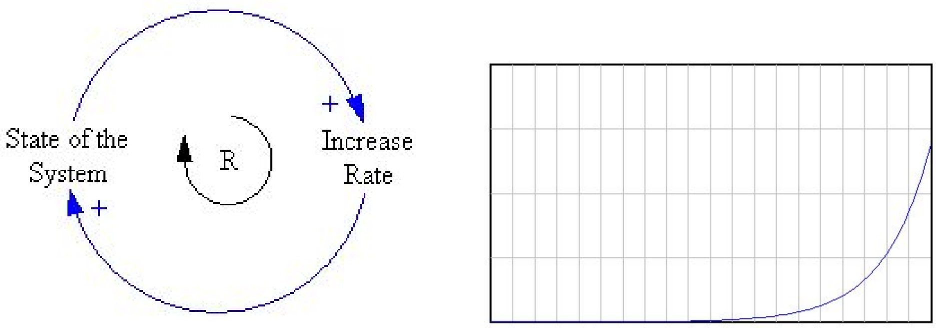
3.5 Structures and Behavior Modes of Dynamic Systems

Feedback loops, delays, and nonlinearities give rise to the basic dynamic behavior modes, which are results of the fundamental structures of dynamic systems. These behavior modes are: *exponential growth*, *goal seeking*, *oscillation*, *s-shaped growth*, *s-shaped growth with overshoot*, *overshoot and collapse*, and *worst-before-better*. The structures behind these behavior modes are in focus, because system behavior is the result of system structure. *Exponential growth*, *goal seeking*, and *oscillation* are the fundamental behavior modes caused by positive feedback, negative feedback, and negative feedback with delay, respectively. The rest of the structures are combinations of these three modes. The nonlinear interaction and loop dominance of these three modes are causing the other behavior modes.

When a specific behavior is observed in a system, an assumption about the structure can be made. When exponential growth, for instance, is observed, there must be at least one dominant positive feedback loop in the system. However, this does not tell anything about the many possible negative feedback loops and non-dominant positive feedback loops. This knowledge can be used to help the modeling process. The overall behavior of the system is a combination of these fundamental behavior modes. [1] [25]

3.5.1 Exponential Growth

Exponential growth (Figure 3.5) is generated by a positive feedback loop. The increase rate increases when the state of the system increases, which eventually leads to increase in the state of the system. This accelerating growth leads to exponential growth. [1, p.108]

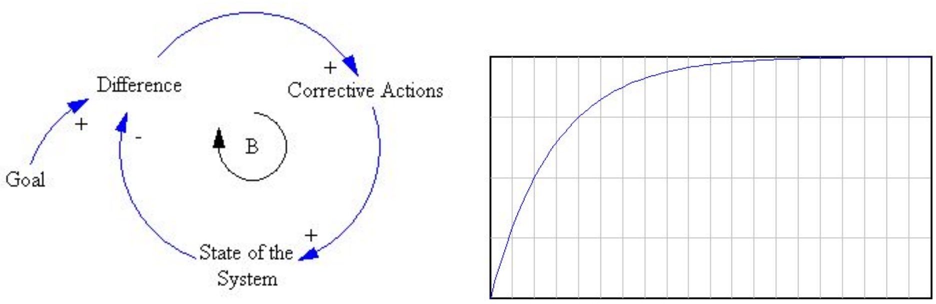


(a) Structure (b) Behavior

Figure 3.5: Exponential growth. [1, p.108]

3.5.2 Goal Seeking

Goal seeking (Figure 3.6) behavior is generated by a negative feedback loop. A negative feedback loop tries to converge towards the goal, which is the desired state of the system. When a difference arises between the state of the system and the goal, corrective actions are taken. [1, p.111]

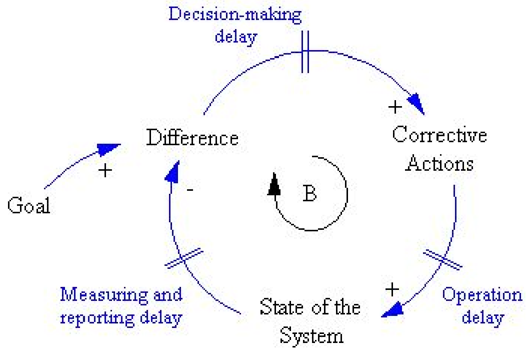


(a) Structure (b) Behavior

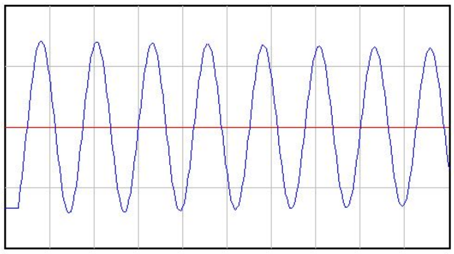
Figure 3.6: Goal seeking. [1, p.111]

3.5.3 Oscillation

Oscillation (Figure 3.7) is generated by a negative feedback loop (goal seeking behavior) with delay. Oscillation always requires a negative feedback loop and a delay. Goal seeking behavior results in convergence towards the goal, but because of delay the state of the system keeps increasing beyond the desired level. This overshooting repeats itself when corrective actions are taken in the opposite direction, thus generating oscillation. [1, p.114]



(a) Structure

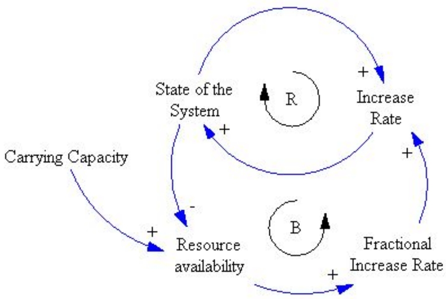


(b) Behavior

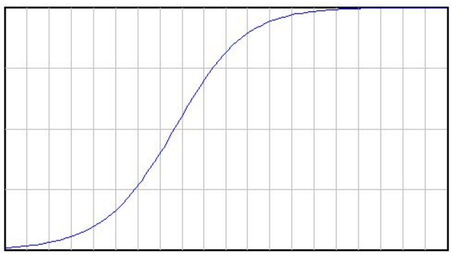
Figure 3.7: Oscillation. [1, p.114]

3.5.4 S-shaped Growth

S-shaped growth (Figure 3.8) is generated by exponential growth and goal seeking. First a positive feedback loop dominates the system generating exponential growth. At some point the carrying capacity limits the growth and the negative feedback loops start to dominate resulting goal seeking behavior, the overall outcome is s-shaped growth. [1, p.118]



(a) Structure

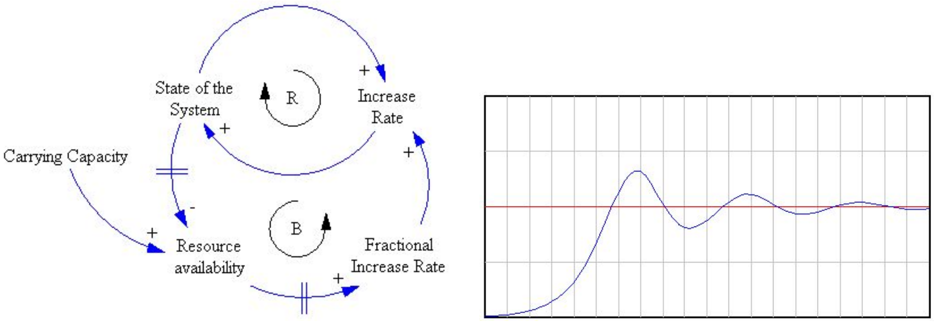


(b) Behavior

Figure 3.8: S-shaped growth. [1, p.118]

3.5.5 S-shaped Growth with Overshoot

S-shaped growth with overshoot (Figure 3.9) is generated by s-haped growth and delay in the negative feedback loop. The system is behaving as the s-shaped growth, but because of the delay in the negative feedback loop the system overshoots. [1, p.121]

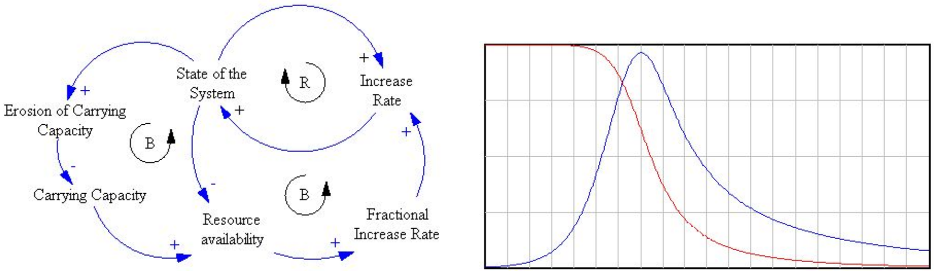


(a) Structure (b) Behavior

Figure 3.9: S-shaped growth with overshoot. [1, p.121]

3.5.6 Overshoot and Collapse

Overshoot and collapse (Figure 3.10) is generated by s-shaped growth and the erosion of carrying capacity. The target of the goal seeking mode (negative feedback loop) is decreasing as the overgrown state of the system consumes the carrying capacity of the system. This leads to overshoot (s-shaped growth) and collapse. [1, p.123]

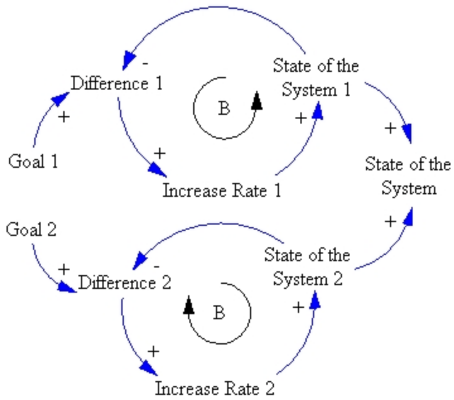


(a) Structure (b) Behavior

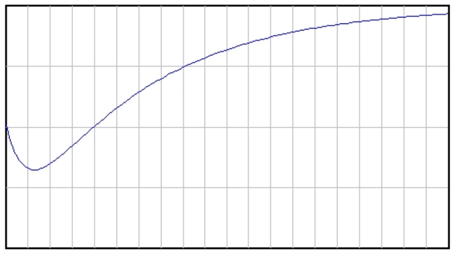
Figure 3.10: Overshoot and collapse. [1, p.123]

3.5.7 Worst-before-better

Worst-before-better behavior (Figure 3.11) is generated by two balancing loops, i.e. two goal seeking structures with different goals. First the upper loop dominates and the system is converging towards the *Goal 1*. At some point the lower loop starts dominating and the system starts converging towards the *Goal 2*. [1]



(a) Structure



(b) Behavior

Figure 3.11: Worst-before-better. [1]

3.6 Models and Modeling

Computer models and especially computer simulations are invaluable when studying the dynamics, interactions, and behavior of systems. Increasing understanding about the underlying system helps to react to the problems and to design the system to work better. Models are generally an easy, cheap, and fast way to test and study the behavior of the system in comparison to working with the real system. [1]

How to be sure that the model is correct? Sterman [1] states that all models are wrong, because all models are only simplifications of the real world. However, everyone uses models, mental or formal, and therefore one should choose the best model available. The goal is to make better decisions, not to model a system detail by detail. There are several ways to validate and evaluate the correctness and usefulness of the model. Models should always be made for solving a specific problem, not just for the sake of modeling. [1, pp.83-104]

Forrester [23] states that when evaluating model validity, its usability for a specific purpose should be evaluated. The validity of the model should be checked in many ways, but Forrester emphasizes that an excellent model in one purpose can be misleading in another situation. This is why the real value of the model is determined by the usefulness of the model and how it increases the understanding of decision makers and how it enables better and more effective decision making. [23, pp.57-59, pp.115-129]

In the validation process of system dynamics models historical data is often used. However, it should be kept in mind that it is improbable that history has revealed all possible behaviors of the system. This is also why the structure of the system is of interest. Structures that have not yet dominated the behavior of the system should also be modeled. Especially in the long-term small changes in the variables can have widespread consequences in the future. [1]

Other validation methods include expert evaluations of the model and the simulation results. Sterman [1] has listed widely used model testing practices, here some of them are presented: boundary adequacy, structure assessment, dimensional consistency, parameter assessment, extreme conditions, integration errors, and sensitivity analysis. For comprehensive list, see [1, p.861].

Often models are large and highly complex both structurally and dynamically. It is important to use clear and illustrative ways to build the models, so that their structure and behavior are easily evaluated and studied.

Modeling is a challenging process. The model should describe the underlying system truthfully, even though not all details can be included in the model. To ensure the best outcome, the modeling process should include professional modelers and experts of the studied matter [1]. System dynamics approach can be condensed as follows [26] [1] :

- Identify the problem.
- State a dynamic hypothesis that explaines the origin of the problem.
- Build the model with the help of experts of the studied matter.
- Test and validate the model. The model should be able to generate behavior observed in the real system.
- Develop the model furthermore and find procedures and modes to solve the initial problem.
- Implement the found solutions in the real system.

System dynamics models are not always the best modeling approach to every situation. It should be kept in mind that system dynamics is only a tool within many other tools although it is proved to be useful in many applications and to increase understanding about the underlying problem, which is not always achieved with other modeling techniques. System dynamics require time and effort from the modeler and from the user.

3.7 System Dynamics in Energy and Electricity Business

Ford [28] has collected a comprehensive list of applications in which system dynamics has been applied to the energy and electricity sector. Utilization of system dynamics in the energy began before the 1973 oil crisis and has continued to this day. Naill [29], for instance, built a national energy model and used it in the US Department of Energy. Ford [30] [31] has studied electric vehicles and their influence on the energy markets. Bunn [32] and Lyneis *et al.* [33] have built models of privatization and deregulation of electricity markets. Dyner *et al.* [34] have analysed electricity market integration. Several other people have used system dynamics to these same topics and to other topics too. For a comprehensive list see [28] and [35].

There have been several interesting attempts to model electricity markets and Nord Pool using system dynamics. Vogstad [36] has used system dynamics to study the Nordic electricity market. This is a comprehensive work of the supply side describing electricity capacity, production, and price formation, although the consumption side is more or less an external variable.

Bucher *et al.* [37] have used the same kind of stock and flow idea which is typical to system dynamics to model Swiss household electricity consumption, especially the appliances with thermal storage. In his study, the aim was to model the propagation of controlling appliances for thermal storage devices, which could be used to shift electricity consumption in time and to reduce peak demand. Bucher also emphasizes the dynamics of propagation of electricity appliances and he states that propagation of new appliance properties (e.g. sophisticated load management methods) is important for estimating the future of possible smart grid applications.

Ford [28] has made interesting observations on why system dynamics is suitable for environmental and business modeling, especially in the electric power industry. He says that the advantage of system dynamics practitioners have compared with others is the ability to see feedback loops. Also the possibility to transfer mental models to a computer and to simulate is a great advantage, especially when illustrating the interactions between the main feedback loops in the system. [28]

Chapter 4

Household Electricity Consumption Habits

This chapter addresses the importance of consumer behavior in the electricity markets. This topic is divided into two sub-topics, short-term and long-term electricity consumption habits. The short-term behavior refers to daily and monthly behavior, while the long-term behavior refers to a longer time horizon, mainly years and decades.

This chapter explains the concepts of the household electricity consumption habits. Section 4.1 introduces the concept of consumption habits and clarifies the definition. Section 4.2 explains the short-term behavior. Section 4.3 explains the long-term behavior. Section 4.4 presents the ideas of the demand response and how it is linked to the short-term and long-term behavior.

4.1 Introduction

Consumer behavior in the electricity markets is a wide topic. Here it refers to how people in households are using their electricity, mainly by appliances. Although electric heating is usually an automated device affected by the outdoor temperature and the indoor target temperature, it can still be seen as consumer behavior especially in the long-term. The consumers can usually choose the target indoor temperature and also affect on the selection of the heating method, e.g. electric, oil, or district heating.

The overall electricity demand, and therefore also the electricity price, has several main trends and profiles, e.g. daily, weekly, and annual. A daily profile (Figure 2.2) illustrates different consumption of every hour of the day, the largest differences depend mainly on the day and night. A weekly profile illustrates the difference between weekdays and weekends. An seasonal profile (Figure 2.3) illustrates the difference between seasons. In this thesis the focus is on the electricity consumption habits that are changing over time, and therefore the focus is on the daily and weekly load profiles and long-term trends. It is reasonable to assume that these two are changing over time, because the daily electricity consumption can change, for instance, if electricity intensive tasks are shifted to night, e.g. electric heating. Shifting loads from weekdays to weekends is not seen as a potential way to reduce the peak demand compared to other methods. Annual electricity consumption is in constant change due to changes in the society itself. The main reasons for the change in annual electricity consumption are also the overall energy savings and investments in new technologies.

The interest to load profiles can be illustrated by the following example. On the 22nd of February in 2010 a MWh of electricity costed more than 1400 euro on the most expensive hour of the day, and on the cheapest hour less than 100 euro. The electricity consumption reached over 14 000 MWh/h and the electricity production was under 12 000 MWh/h at the lowest. Price peaks of this kind are possible even though the consumption peaks are relatively mild. Fortunately, these kinds of price peaks are not common. The problem arises from the limits of the capacity sets. At the moment 14 000 MWh/h is near the physical limits of the electricity production capacity combined with the transmission connections, which leads to high prices. The electricity supply capacity is adjusted to peak loads, if the peak loads were decreased, then there would not be as large need for reserve supply sources.

4.2 Short-term Behavior

The daily rhythm is an important characteristic of electricity consumption. Inhabitant's daily rhythm affects the hourly consumption, for example people wake up in the morning and turn on the lights etc. Then most people go to work or to school, which means a shift in the electricity consumption from home to work. After work in the late afternoon people come back home and turn the home appliances on again. The household electricity consumption is mainly driven by the time people spend at home. Figure 4.1 presents how household electricity consumption is divided by appliances on every hour of the day on average [20].

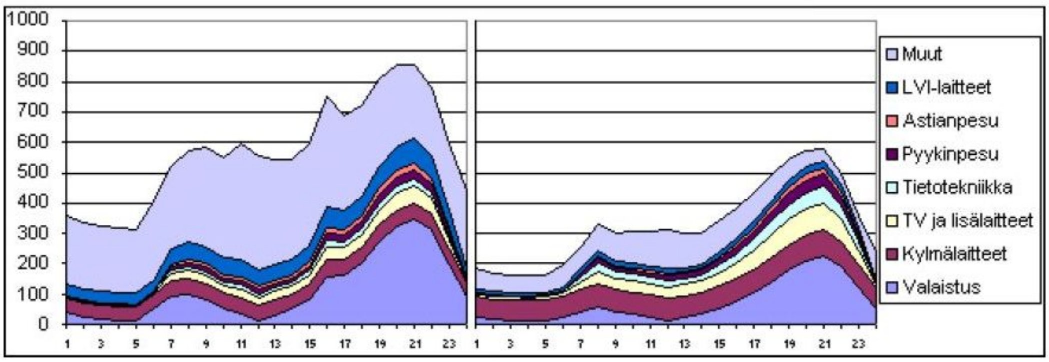
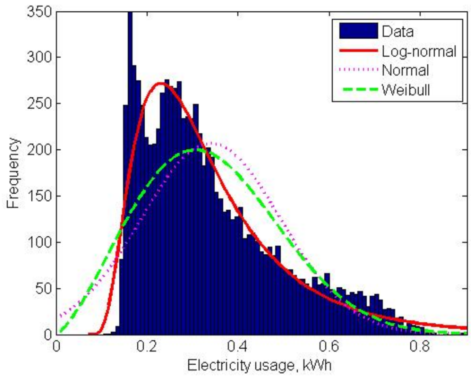
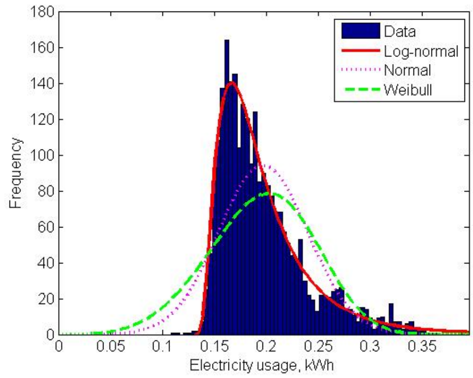


Figure 4.1: Household appliance load profiles. Left: detached household (without electric heating). Right: Apartment (without electric heating). X-axis shows hours and y-axis watts. Appliance groups from top: others, HVAC, dishwashing, laundry, IT, TV, refrigeration, lighting. [20]

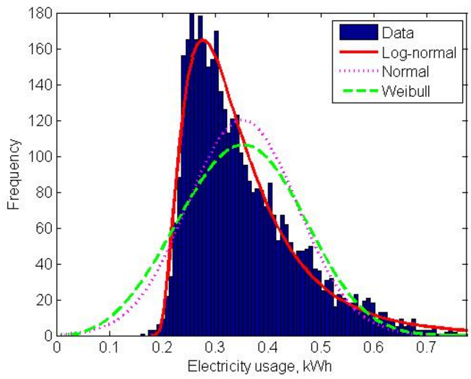
Figure 4.2 presents a histogram of district heated households electricity consumption [38]. The x-axis presents the measured hourly electricity consumptions. The y-axis presents how often a given electricity consumption is measured in the data set. Mutanen *et al.* [38] propose that household appliance electricity consumption is composed of different distributions, mainly log-normal. These distributions reveal fundamental properties how people consume electricity, and this information can be used in the model validation. These characteristics are also been studied by Seppälä [39]. Figure 4.2a presents the histogram of daily consumption, Figure 4.2b, Figure 4.2c, and Figure 4.2d present the same data divided into time segments, 00-07, 07-18, and 18-24, respectively.



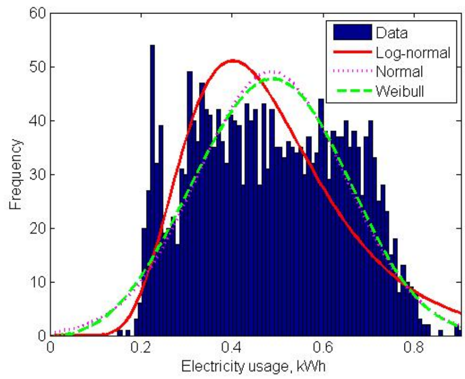
(a) Hours 00-24



(b) Hours 00-07



(c) Hours 07-18



(d) Hours 18-24

Figure 4.2: Histograms of hourly electricity consumption of district heated households. [38]

Household heating electricity consumption depends mainly on the outside temperature and heating method, for instance: direct electric heating, storage electric heating, etc.

One important characteristic of household electricity consumption is time of the year. In Finland and in the other Nordic countries during winter electricity is used for heating and lighting and the consumption is substantially higher than in summer. In warmer countries the household electricity consumption peak can be in the warmest season in summer when air-conditioning is used.

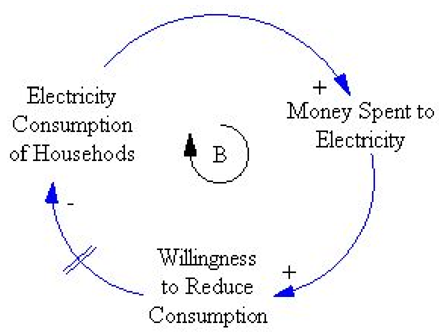
4.3 Long-term Behavior

This section explains how electricity consumption habits are changing in the long-term. The long-term changes can be seen in two ways, i.e. how the hourly load profile and how the total annual consumption change over time.

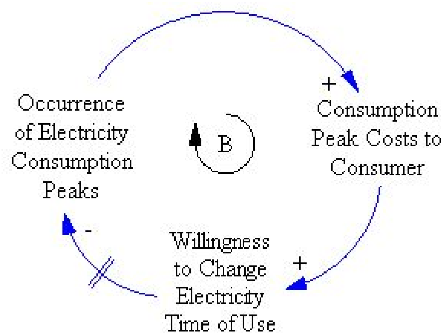
Figure 4.3 presents a causal loop diagram of the long-term behavior of electricity demand and peak demand. Increase in electricity consumption increases the amount of money spent on electricity, which on the long-term increases the willingness to reduce consumption, which restricts the consumption. This balancing feedback loop can be seen in Figure 4.3a.

The same balancing phenomenon appears in peak demand reduction as seen in Figure 4.3b. When unwanted peak demand occurs and the costs are transferred to consumers, willingness to change the time of consumption increases, thus reducing peak demand. If the incentive to reduce peak demand disappears in the long-term, then peak demand will increase again. At the moment peak demand reduction is not working properly, because the price changes are not transmitted to customers directly.

These both negative feedback loops have significant time delays, which indicates that these systems can oscillate. However, there are many other things affecting electricity demand too.



(a) Restricting demand



(b) Peak demand

Figure 4.3: A long-term development of the demand and peak demand.

The flatter the electricity price, the less incentive customers have to change their behavior, or they might even change their behavior back to the original. This can be taken into consideration in the system design by changing the tariff structure steeper against small changes in the electricity prices. In other words, if today a 10% increase in the spot price increases the consumer price 10%, in 10 years a 5% increase in the spot price could increase the consumer price 10%. Designing the system this way would retain the economic incentive to change the time of use. So far the price mechanisms have been inadequate, but this can change rapidly due to smart meter installations.

Currently, residential consumers are not encouraged enough to change their behavior habits and they do not have enough information about their current electricity consumption, electricity price, and how to reduce electricity consumption and what the benefits are. Smart meters and the smart grid will solve several obstacles and allows more dynamic consumer behavior.

Figure 4.4 presents a histogram of the annual electricity consumption. Mutanen *et al.* [38] propose that annual electricity consumption is log-normally distributed. This knowledge can be used in model validation. The x-axis presents the measured annual electricity consumptions. The y-axis presents how often a given annual electricity consumption is measured in the data set. The data set consists of 19301 consumers. The same phenomena has also been studied by Kolter *et al.* [40] with similar kind of results.

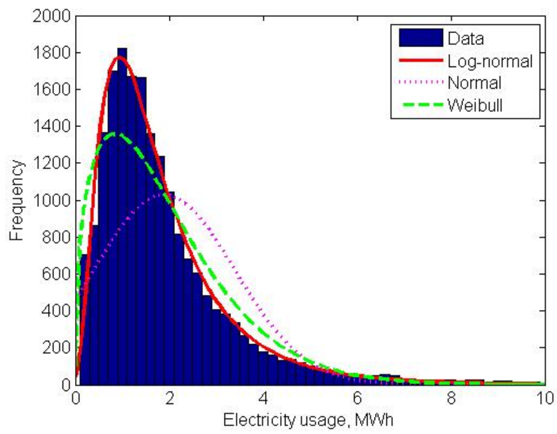


Figure 4.4: Histogram of the annual electricity consumption of 19301 consumers. [38]

The interesting and not a trivial question is, how much household electricity consumption can or is likely to change in given time horizon? Long time delays and inertia in the system make it difficult to understand how fast the electricity consumption can change. This question is studied more carefully in Chapter 5.

4.4 Demand-side Management

Demand-side management (DSM) usually refers to a situation where the electricity time-of-use is wanted to shift or the overall consumption to decrease. The objective of demand response (DR) programs is to shift consumption from high demand to lower demand periods. [41]

The most usual way to change consumption habits is an economic incentive, i.e. the price; also social and moral incentives affects the behavior. However, it seems that consumer responses to the electricity price changes are not always significant, which is understandable when considering the minor savings of a small district heated household for instance.

One problem has been the lack of information. Due to the old invoicing system customers receive real information about their consumption only once a year, and the price of electricity is changing only a few times per year. Residential customers will not be able to manage their electricity consumption, if they do not have information about their consumption. DSM also has to be effortless for the customer. [42]

The tariff is key to demand response. In Finland, different tariff structures have been tried several times in the last few decades. Most common tariff structure has been a constant price for all times. There has also been time-of-use (ToU) pricing methods, where usually day and night tariffs are different, but also weekday/weekend and summer/winter tariffs have been used.

Borenstein [19] claims that even though the ToU pricing is in active use, it does not give enough economic incentives to affect behavior and reduce the peak loads. Real-time pricing (RTP) would be a quite natural way to shift the fluctuation in the price straight to the customer. However, this does not solve the problem completely since the consumers do not want these kinds of tariff structures due to the unpredictability of the price. [19]

It has been claimed that demand response in general can reduce the peak demand and price significantly. A less volatile demand and price would benefit many parties in the electricity business. The smart grid on the other hand enables the use of demand response applications, although it does not solve the problem without economic and environmental incentives. [19] [43]

Figure 4.5 presents a simple draft of demand side management by Davito [41]. As seen in the figure, demand side management consists of load shifting and energy efficiency. Borenstein and Davito both emphasize the importance of customers' involvement and how the demand side management should be made more tempting. Davito has summarized the requirements for successful demand side management, which include economic incentives, suitable tariff structure, and willingness to use these. [19] [41]

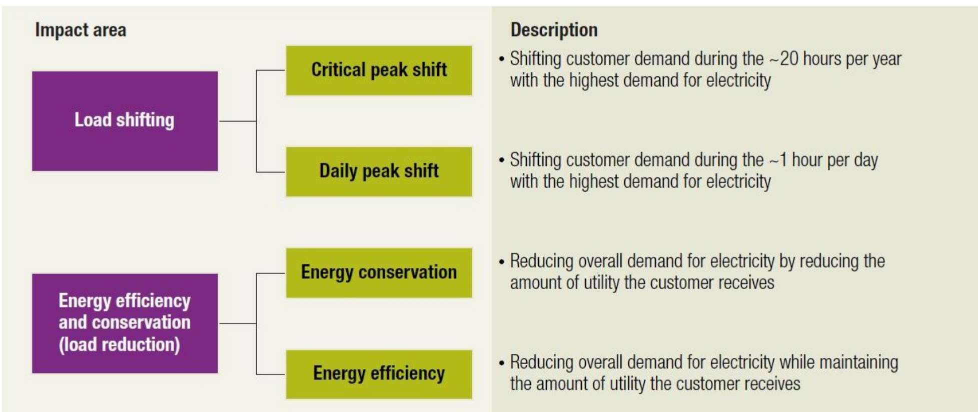


Figure 4.5: Demand side management. [41]

Because of the RPT-pricing disadvantages a Critical peak pricing (CPP) could be a good compromise between TOU- and RTP-pricing. It has some benefits of the RTP-pricing, but it still gives enough predictability to the customers. For more about tariff structures, see [43].

Chapter 5

Long-term Electricity Consumption Model

Household electricity consumption can be divided into heating (and cooling) and appliances. Demand for heating is changing slowly due to the slow circulation of the dwelling stock. Household appliance demand is a slightly more complex process, since it consists of slow and fast changing parts and the energy efficiency can change rapidly. For instance, lighting equipment circulation speed is currently relatively fast, i.e. around two years, because of the short lifetime of incandescent lamps. When energy saving lamps and LED-lamps become more wide spread, the average lifetime of lamps increases, therefore affecting the circulation of the appliance stock. On the other hand, refrigeration device circulation speed is relatively slow, i.e. 20 years. This means that different behavior and policy changes affect electricity consumption with a delay, but the delays of different appliance groups are different. In this chapter, a model is formed to understand the phenomenon and dynamics of electricity consumption better.

System dynamics is a good method of understanding complex dynamic problems. Electricity demand changes have several long delays, and understanding these is important when sketching how electricity demand will change in the future.

This chapter presents the long-term model describing the evolution of household electricity consumption. Section 5.1 gives a general overview of the topic. Section 5.2 introduces the general structure of the model. Section 5.3 gives a detailed description of the model. Section 5.4 presents the validation methods and results of the model. Section 5.5 introduces two different scenarios gained using the model. Section 5.6 discusses the future research needed to be done.

5.1 Problem Articulation

Some studies and models related to electricity markets, e.g. the research of Jäger *et al.* [44] and Vogstad [36], are not taking residential customers into account in great detail. This is not a problem in most of the cases because many studies concentrate on supply side and price changes, therefore the supply side is more important to be modeled in detail. The role of consumers is increasing in the future because of the smart grid and future electricity applications. Especially the choices of customers are relevant to the overall system behavior, e.g. there are consumers choosing ground source heat pumps over direct electric heating and then there are consumers willing to adopt demand side management applications. There are several key components affecting the change in overall electricity consumption, e.g. population growth, the average size of households, the amount of appliances, the amount of dwellings, economic growth, the heating methods of dwellings, the energy efficiency of dwellings and the energy efficiency of appliances.

As already explained in Chapter 3, system dynamics is a method of modeling the structure and behavior of complex systems. System dynamics is based on the assumption that the structure defines behavior and therefore the focus should be studying the system as a whole. Therefore, using feedback loops, nonlinearities, delays, stocks and flows it is possible to take into account important parts of the system to describe how they interact with each other. This is why the whole electricity market is modeled roughly, even though the households are in focus. Excluding the electricity capacity and the production would exclude important feedback loops affecting the electricity price, and therefore the model would lack the interaction between the production and the consumption. Also, taking into account the industrial and service sector demand is desirable, since household demand accounts for roughly one quarter of the total demand in Finland. Therefore the industry and service sector affect the capacity and electricity price significantly. Other countries in Nord Pool are left outside of the study, even though it would be justified to include them in the model as well.

In this model, the overall change in electricity demand and the question on how the inertia of the system affects the propagation of new technologies are investigated. The amount of smart grid enabled appliances in the households is crucial for the development of the smart grid business.

Household electricity consumption is changing over time. People are purchasing increasing amounts of appliances, but at the same time the energy efficiency of appliances is increasing. Household electricity consumption for heating (and cooling) is increasing due to increasing amount of households (an increase in population and a decrease in inhabitants per household), but on the other hand the consumption is decreasing, because of energy efficient solutions, e.g. heat pumps and better insulation. This can result in different total electricity consumptions.

It is also worth emphasizing that the model to be constructed is not about modeling the price of electricity. Electricity production capacity and electricity price are important parts in the feedback loop controlling the electricity system; they are taken into account in the model, but not to indicate the possible price shifts in Nord Pool. This work concentrates on the demand side; the production side is more crucial when modeling the price of electricity.

5.2 Structure of the Model

The created model is a combination of the physical structures of electricity markets and human behavior. No equilibrium is assumed although long-term equilibrium is possible. The assumptions on decision-making in the model are based on bounded rationality, and therefore no optimal decision-making is assumed.

In this section the structure of the model is explained in general using causal loop diagrams. The model boundaries and simplifications are also explained.

5.2.1 Simplifications, Assumpitions, and Model Boundaries

A model is always a simplification of the real world. The aim is not to model all the details in the electricity business. The key to a useful model is the ability to make reasonable simplifications; the goal is to model the most important parts and structures of the system. There are also many assumptions made in the model considering both the structure and the variables. Modeling is an iterative process and one's views can be changed and assumptions corrected if required. Many assumptions, i.e. parameter values, are left for the model user to be changed.

Table 5.1 presents endogenous, exogenous, and excluded variables. Not all variables are important for the system; the endogenous variables are the most important, since they depend on the state of the system. The exogenous variables affect the system, but they are not affected by the feedback loops in the model, i.e. they are not affected by the state of the model. The excluded variables are not taken into account. However, if the model is further developed, excluded variables can be included, if required.

Table 5.1: Endogenous, exogenous, and excluded variables.

Endogenous Variables	**Exogenous Variables**	**Excluded Variables**
Household consumption	Population	Energy resources
Electricity price	GDP	Carbon emissions
Expected electricity price	Average Income	Electricity price vs.
Production capacity	Environmental consciousness	other energy prices
Capacity Utilization	Household average size	Summer houses
Amount of Appliances	Industrial demand	
Amount of dwellings	Service sector demand	
Heating methods	Transfer costs	
Energy efficiency	Electricity taxes	

5.2.2 Causal Loop Diagram of Nord Pool

The general causal loop diagram presented in Figure 5.1 describes the physical structure of Nord Pool, as it has been described in Chapter 2. This includes capacity, production, the price mechanism of Nord Pool, and electricity demand (household, industry, and service sector).

Total household electricity consumption affects the electricity price, but so does industrial and service sector consumption; the industrial and service sector electricity consumption is required in the model at a certain level. The price formation is dependent on the capacity, production, and consumption, and therefore capacity and production are required in the model.

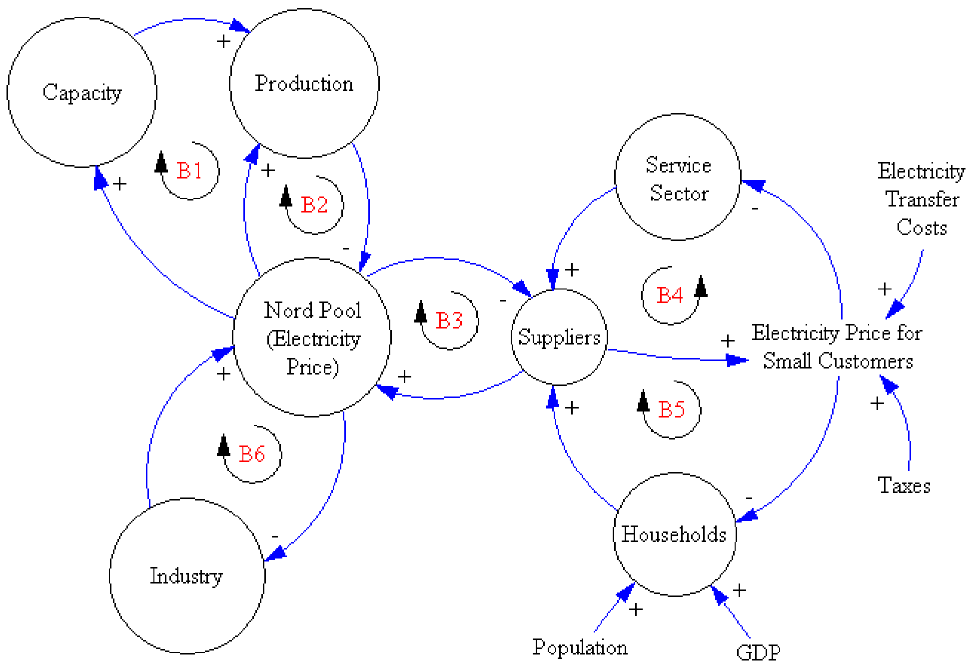


Figure 5.1: Main interactions of market participants and main feedback loops of Nord Pool.

Next the most important feedback loops of Nord Pool are explained.

B1 Capacity Acquisition: Acquisition of new capacity is based on the expected profitability of the new capacity. The capacity enables an increase in electricity production, thus decreasing the price of electricity. This is a balancing feedback loop with significant delays due to the construction delay when building new capacity. This loop might cause oscillations to the amount of capacity and to the electricity price.

B2 Production Control: The higher the price of electricity the more electricity is generated. The more electricity is generated the cheaper the electricity is, therefore a balancing loop.

B3 Demand Control The price of electricity affects the electricity demand of small customers, which feeds back to the electricity price. A more detailed description of this balancing loop is given later.

B4 Service Sector Control: Loop B4 is the same as loop B3, but describing only the service sector demand.

B5 Household Control: Loop B5 is the same as loop B3, but describing only the household demand. A more detailed description of this balancing loop is given later.

B6 Industry Control: The cheaper the electricity, the more the industry is using it. The more industry is using electricity the more expensive electricity is. This balancing feedback loop has significant delays due to the construction delay of new industry capacity, and therefore this loop might cause oscillation in the electricity price and industry capacity depending on how much the industrial demand is changing over time.

Conclusion: As seen in Figure 5.1, the most important feedback loops describing Nord Pool are balancing loops. This indicates that the system is trying to converge to equilibrium, however, this does not mean that the system ever reaches an equilibrium, or that there is a stable equilibrium. The system can also, for instance, converge to a limit-cycle (stable oscillation) if such exists. Especially external perturbations, e.g. in population, GDP, etc., keep the system in motion. Also small perturbations can be enough to maintain oscillation. However, this is more a problem of the supply side than the household consumption side, because the electricity price is not transferred directly to households, at least not yet.

5.2.2.1 Supply Side

Figure 5.2 presents a more detailed causal loop diagram of the supply side. This includes capacity, production, price formation, and demand in general. In the figure can be seen same feedback loops as in Figure 5.1: Loop B1 in Figure 5.2 corresponds to loop B1 in Figure 5.1 and loop B3 in Figure 5.2 corresponds to loop B2 in Figure 5.1.

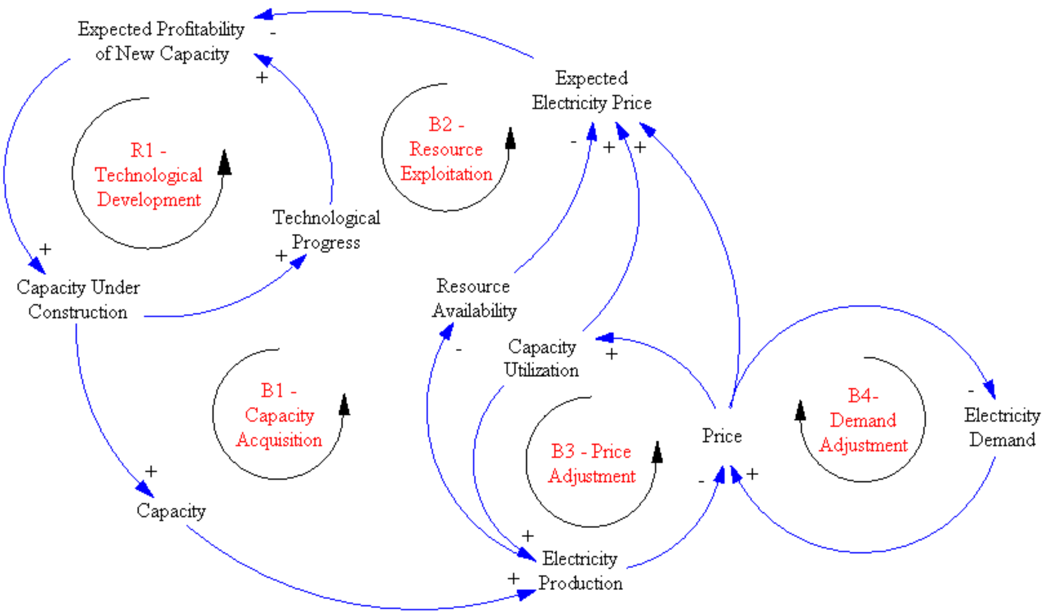


Figure 5.2: Simplified structure and main feedback loops of the supply side.

B1 Capacity Acquisition: The same feedback loop as loop B1 in Figure 5.1. Investments into new capacity are based on the expected profitability of the new capacity. The expected profitability depends, among other things, on the expected electricity price, which depends on the electricity price, capacity utilization, and resource availability. These are all affected by the electricity production and thus the capacity itself. This balancing loop keeps the amount of capacity at a reasonable level. However, due to the delays in the new capacity construction, this balancing loop might cause oscillation in capacity.

B2 Resource Exploitation: Resource exploitation is an important feedback loop in the long-term. The more electricity is produced the more resources are exploited, which is likely to have major impacts on the electricity production in the long-term. This depends of course on the structure of the production capacity and how it is adjusted in the coming decades. If production is based on nonrenewable energy sources, then this loop is likely to cause limitations to the production. However, this is not in the scope of this thesis, and therefore this feedback loop has been excluded from the final model.

B3 Price Adjustment: The electricity price is determined based on demand and supply. If price increases, then capacity utilization increases. If capacity utilization increases, then productions increases. If production increases, then the electricity price decreases, thus completing the balancing feedback loop. Because of the time horizon of the model, 50 years, the price formation is not modeled in as much detail as it really is. Simplifications are made and short-term price fluctuations, such as seasonal fluctuations in the price, are neglected.

B4 Demand Adjustment: Long-term increase in the electricity price decreases electricity demand. Decrease in demand on the other hand decreases the price, therefore a balancing loop. This loop is explained in more detail later.

R1 Technological Development: Technological development increases the expected profitability of new capacity due to the decreased production costs and decreased release of pollutants. Expected profitability increases the willingness to make investments into new capacity. Building new capacity furthermore boosts the development of new technologies. This is a reinforcing loop. However, this is not likely to cause a vicious cycle and collapse the expertise in technological knowhow. A rapid growth is also not likely, but it is possible. Solar energy and wind power are currently the rapidly growing areas in electricity production technology. Nonetheless, technological development is likely to keep growing.

Conclusion: The supply side model is kept simple intentionally. The model is able to catch the dynamics of the electricity price, capacity and production, without going into too much detail. Of course, due to the limitations it is not sufficient to analyse the production side, e.g. capacity development and production methods.

5.2.2.2 Household Demand

Figure 5.3 presents a more detailed causal loop diagram of the demand side. The demand side model describes how households are reacting to price changes and increases in demand in the long-term. Different incentives (economic, social, moral) are driving decisions on how electricity is consumed. Technological development changes the electricity consumption in the long run, and the ongoing trends of population growth, household size growth, increase in appliance acquisition, increase in energy efficiency etc. are affecting the consumption, and are therefore taken into consideration in the model.

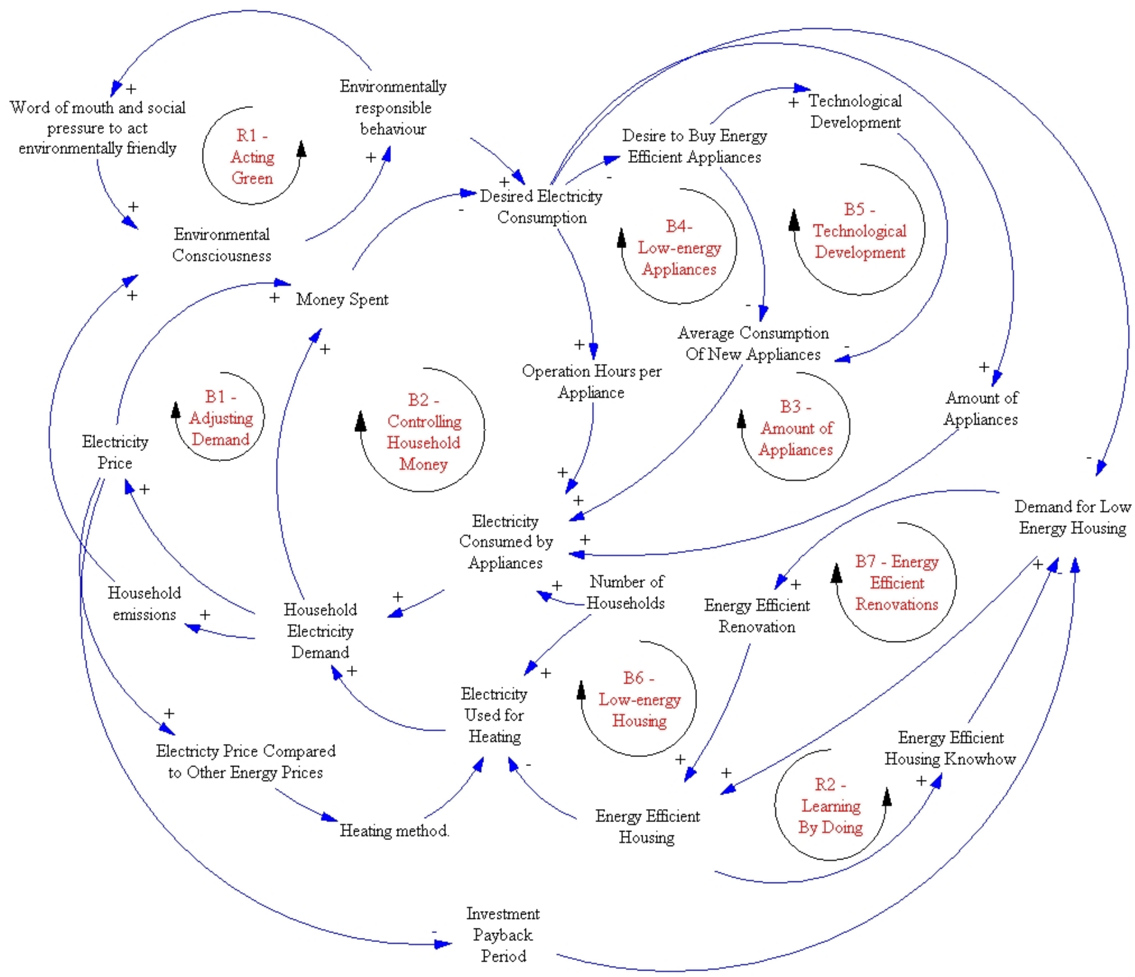


Figure 5.3: Simplified structure and main feedback loops of the household demand side.

B1 Adjusting Demand: An increase in the electricity price increases the amount of money households are spending. An increase in the amount of money spent on electricity decreases the desired electricity consumption. This finally leads to decrease in electricity consumption by appliances and heating thus decreasing the total household electricity demand. Decreased demand decreases the electricity price. However, this balancing feedback loop is not the most important from the households' point of view, since the effect of household demand on the electricity price is quite mild in the long-term, because total household electricity demand counts only for one quarter of the total demand. Also the electricity price is roughly one-third of the total bill due to the transfer costs and taxes.

B2 Controlling household money: This is almost the same loop as B1. Increase in the amount of money spent on electricity decreases the desired electricity consumption. This finally leads to decrease in electricity consumption by appliances and heating thus decreasing the total household electricity demand. Decreased demand decreases the amount of money spent on electricity. Compared to the loop B1 this is much more relevant; decisions are affecting the amount of money spent directly. This loop can also be seen as willingness to shift operation time of appliances. This is possible if new tariff structures are introduced. However, shifting the appliance time of use does not change the overall electricity consumption.

B3 Amount of Appliances: This is partly the same as B1 and B2. Decrease in desired electricity consumption decreases the amount of appliances purchased, which decreases the household electricity consumption.

B4 Low-energy Appliances: Decrease in desired electricity consumption increases the desire to buy energy efficient appliances, which leads to decrease in household electricity consumption.

B5 Technological Development: Technological development describes how the demand for energy efficient appliances increases the investments in new energy efficient technologies.

B6 Low-energy Housing: Increase in desired electricity consumption increases the demand for low energy housing, which increases the building of new energy efficient housing. Energy efficiency in housing is also affected by consumer demand, which depends on household money used for electricity.

B7 Energy Efficient Renovations: This is part of the loop B6. Increases in the demand for low energy housing increase the amount of energy efficient renovation people are willing to do. This leads to increase in energy efficient housing, which will eventually decrease the electricity consumption.

R1 Acting Green: This describes the reinforcing loop in how environmental consciousness increases the environmentally responsible behavior, which furthermore affects the word of mouth and social pressure, thus increasing the environmental consciousness. This can lead to exponential growth or collapse in environmentally responsible behavior. This feedback loop is excluded from the final model due to the difficulty of modeling and lack of data. However, already by studying the causal loop diagram interesting scenarios can be seen. If household emissions are reduced significantly, for example due to an increase in renewable energy production, the incentive for environmental consciousness is decreased, and therefore a vicious cycle is possible in the loop, resulting in a collapse in environmentally responsible behavior.

R2 Learning by Doing: Increase in energy efficient housing decreases the costs of building a low energy house and a low-energy renovation. This loop is excluded from the model due to lack of data.

Conclusion: Energy consumption in households is an interesting process. Most of the feedback loops described are not likely to affect the electricity consumption greatly, although they have some effect, especially in the long-term. In some cases, e.g. a one-room flat, households consume relatively small amounts of electricity, and possible savings due to behavioral changes are minimal. Therefore, in some cases environmental incentives might have a greater impact than economic incentives. For better simulation results, the model could be segmented to cover different consumer segments, e.g. price-conscious and ecologically-conscious consumers. Also heating method segments and household type segments could be used to determine more accurately what the benefits of saving electricity are, since an electrically heated detached house has more incentives to save electricity than a district heated one-room flat.

It is not likely that the behavior of small apartment houses will change substantially, especially if district heating is used. At least money will not be the main motive to use less electricity in these cases. Increasing environmental consciousness might have a larger impact on consumers who cannot save money.

5.3 Detailed Description of the Model

In this section, the structure of the model is explained in detail using stock and flow diagrams. The model is divided into seven submodels: *dwelling stock*, *appliance stock*, *desire to conserve electricity*, *electric vehicles*, *supply side*, *propagation of smart meters and the effect of information*, and *environmental consciousness*. Simplified stock and flow diagrams are presented here, for the original diagrams see Appendix B.

5.3.1 Dwelling Stock

The dwelling stock and the energy consumption of dwellings is modeled using *aging-chain* [1, p.470] and *co-flow* structures [1, p.479]. Aging-chain describes the aging process of the dwelling stock, Figure 5.5, whereas co-flow catches the energy consumption of these dwellings, Figure 5.7.

Figure 5.4 presents a causal loop diagram of the dwelling stock and Figure 5.5 describes the stock and flow diagram of the dwellings.

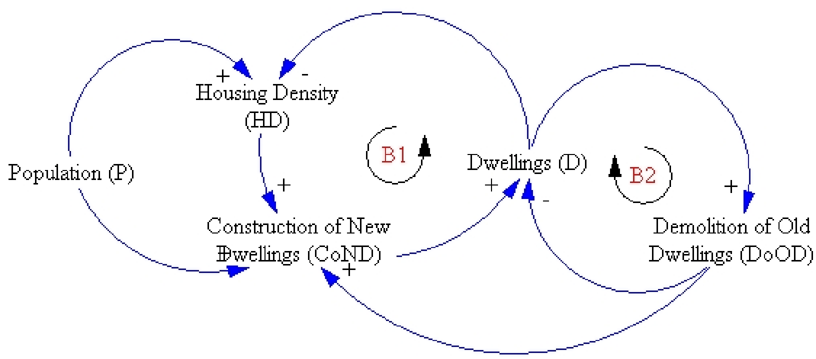


Figure 5.4: Causal loop diagram of the dwelling stock.

Dwelling stock is described by a series of first order delays. Three first order delays form an aging chain of third order delay, as seen in Figure 5.5. Constructing the model this way enables to keep track on the amount of dwellings, which are divided into detached, row, and apartment houses. All these groups are furthermore divided based on the heating method, which are divided into electric, districts, oil, biomass heating, and ground source heat pumps (GSHP). Electric heating could further be divided into direct and storage heating.

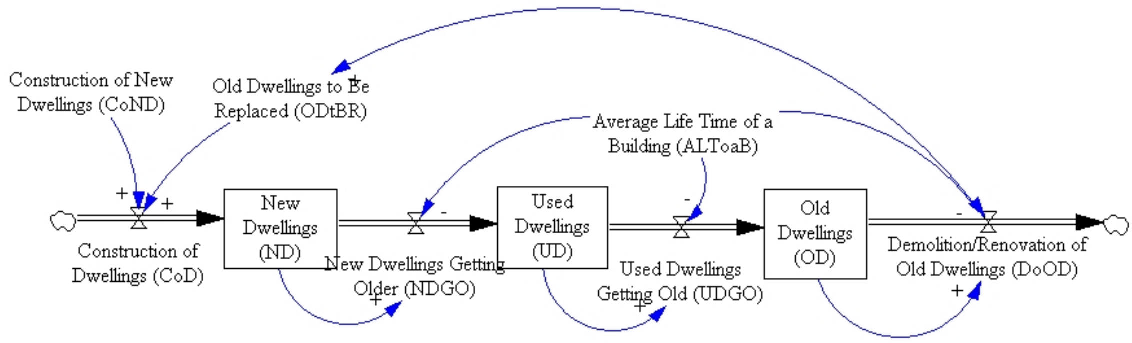
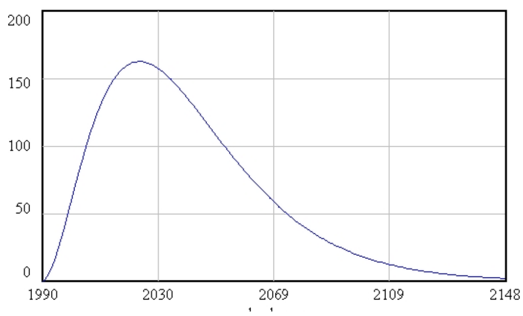
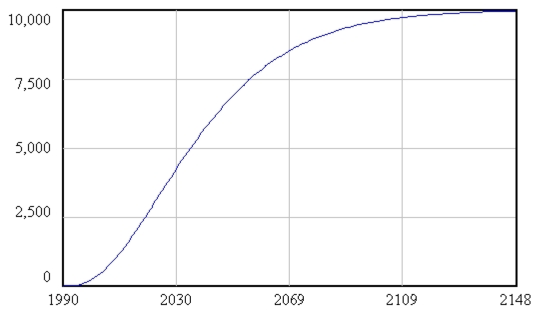


Figure 5.5: Aging-chain of the dwelling stock.

When a new dwelling is constructed, it enters a dwelling stock, which is described by an inflow *Construction of Dwellings*. The dwelling stays in the dwelling stock, *New Dwellings*, *Used Dwellings*, and *Old Dwellings* until it is demolished. Demolition is described by an outflow *Demolition of Old Dwellings*. The average lifetime of a building describes how long a dwelling is in the dwelling stock on average. The lifetime distribution and cumulative lifetime distribution of a dwelling stock is given in Figure 5.6. The figure shows how the demolition/renovation of 10 000 houses constructed in 1990 is distributed given that the average life/renovation time is 50 years. The inertia of the dwelling stock has been analysed more carefully in the work of Pruyt *et al.* [45].



(a) Lifetime distribution



(b) Cumulative lifetime distribution

Figure 5.6: How demolition or renovation of 10 000 houses constructed in 1990 are distributed given that the average life/renovation time is 50 years. X-axis shows the year and y-axis denotes number of dwellings.

Figure 5.7 presents how the energy consumption of dwellings is modeled using aging-chain and co-flow structures. When a dwelling is constructed, the heating it consumes is stored to another aging-chain and when a dwelling is demolished, the heating it consumes is removed from the heating stock. This allows taking into account that older dwellings consume more energy than newer ones. The heating consumption of a dwelling depends on the average energy consumption per m^2 and the average floor area. Both energy consumption and floor area are changing over time.

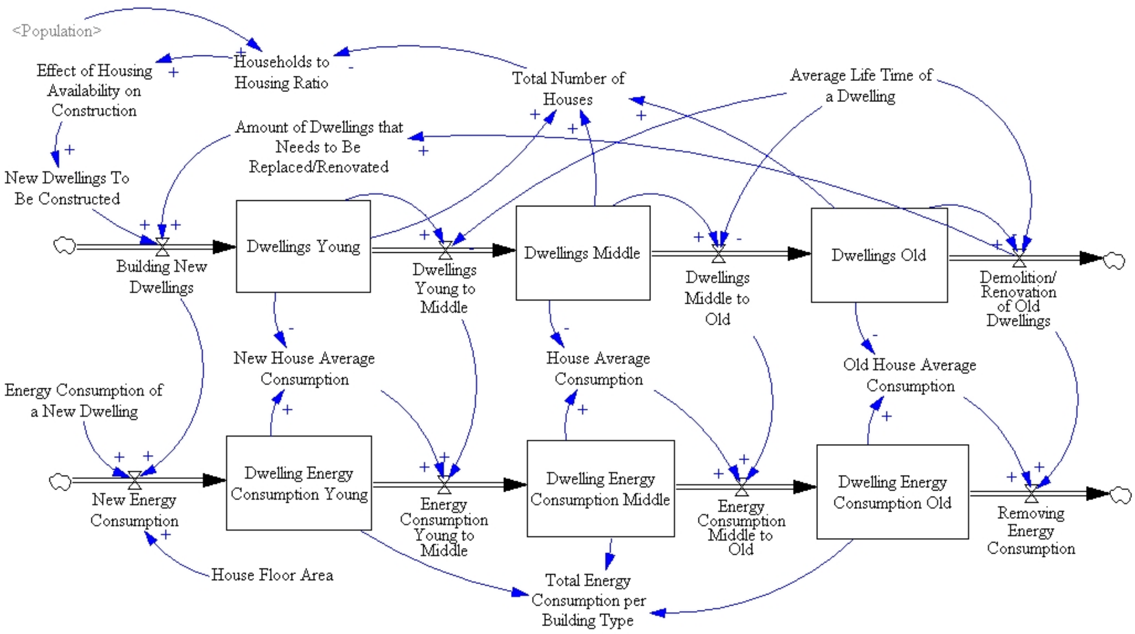


Figure 5.7: Dwelling stock and electricity consumed by dwellings.

In the model renovations and demolitions are not distinguished. The energy consumption is under interest, and therefore it does not matter if the dwelling is demolished and a new dwelling is built or if the dwelling is renovated using new regulations. Renovated dwellings are not as good as new ones, and therefore a parameter is added to compensate this flaw. The model is working and it is kept as simple as possible. Nevertheless, more accurate results could be achieved by separating demolitions and renovations.

The average lifetime of 50 years is used in the model. This is a rough estimate, because data on the average lifetime is scarcely available and demolitions and renovations are not distinguished. This parameter can be changed by the model user.

5.3.2 Appliance Stock

The appliance stock, seen in Figure 5.8, is modeled in the same way as the dwelling stock, using aging-chains and co-flows. When appliances are purchased, they enter the *New Devices* -stock. After one third of the average lifetime has passed, they enter *Used Devices* -stock. Again after one third of the average lifetime they enter *Old Devices* -stock. Finally after one third of the average lifetime the appliances are recycled. This is a third order system by which it is possible to model how long an appliance is in the appliance stock on average. When the consumer purchases an appliance now, it will take on average X years before a new appliance is purchased, even if a new low energy appliance is introduced just after the purchase. The average lifetimes of appliances are introduced in the Adado report [46].

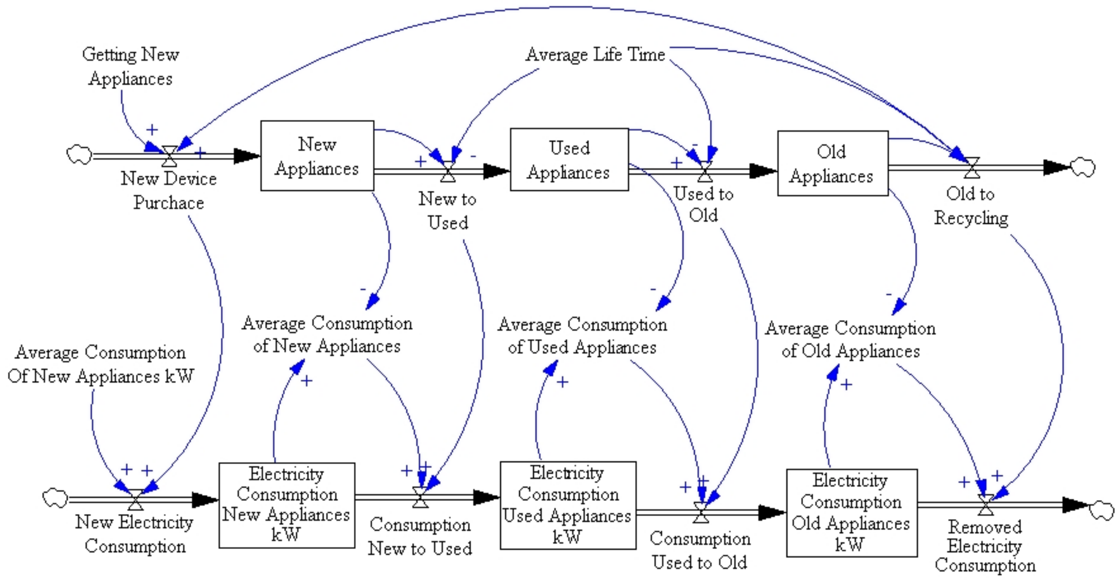
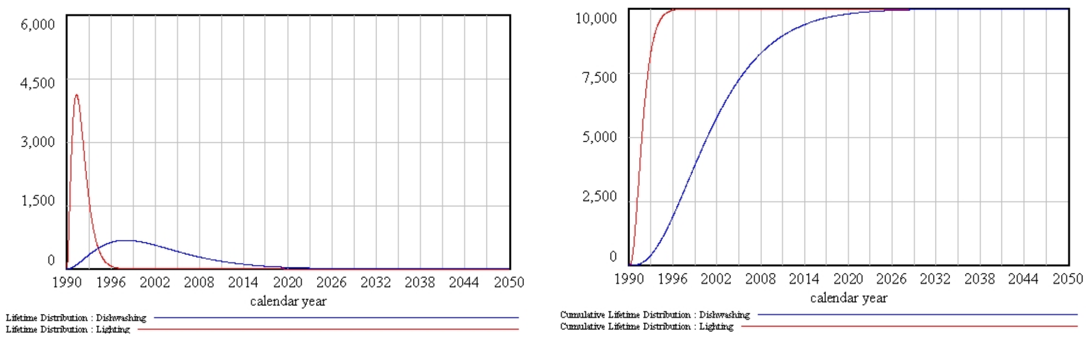


Figure 5.8: Appliance stock and appliance stock electricity consumption.

Appliances are currently divided into different subgroups, e.g. lighting, car heating, sauna, HVAC (heating, ventilation, and air conditioning), entertainment, laundry, cooking, refrigeration, and floor heating; every appliance group is modeled separately with different parameters. Figure 5.9 presents how the lifetimes of different appliances affect the lifetime distribution, lighting and dishwashing are taken as examples. The lifetime of an incandescent bulb is assumed to be two years and the lifetime of a dishwasher 12 years.



(a) Lifetime distribution (b) Cumulative lifetime distribution

Figure 5.9: The plots show how recycling of 10 000 appliances purchased in 1990 are distributed given that the average lifetime for lighting devices is two years and twelve years for dishwashers.

5.3.3 Desire to Conserve Electricity

Consumer behavior is an ambiguous but important phenomenon to model. Figure 5.10 presents how desire to conserve electricity is modeled.

Desire to conserve electricity affects how willing people are to purchase energy efficient appliances and low energy housing. Therefore it is an interesting and important variable, which is very difficult to model. The desire to conserve electricity is modeled using several variables, in the model it depends on *Electricity bill relative to income*, *Effect of information*, *Environmentally responsible behavior*, and *Experienced Value of Electricity*.

When consumers have more information available on their consumption, they can change their consumption habits. Consumers also react to the changes in the electricity price, but currently electricity price for households does not vary much. This could change if new tariff structures was introduced.

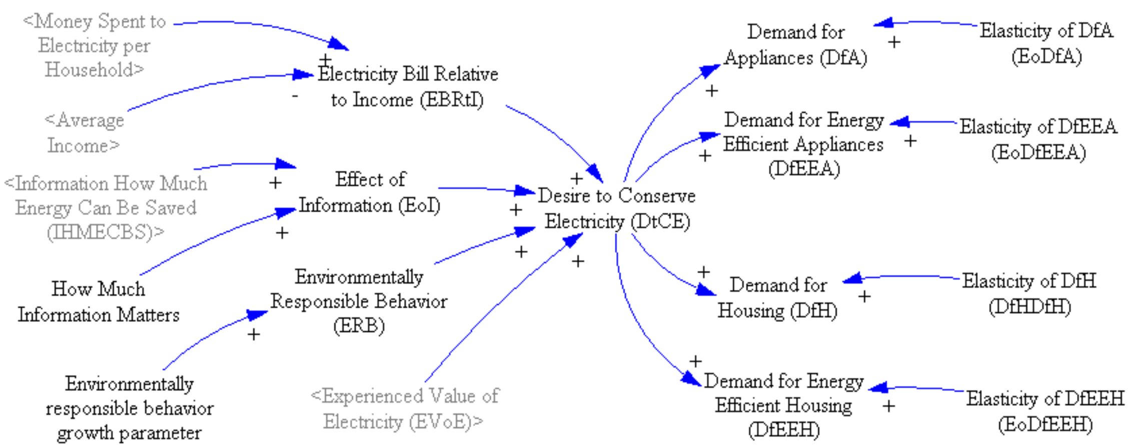


Figure 5.10: Desire to conserve electricity.

Eq. (5.1) presents how *Desire to Conserve Electricity* is modeled, a multiplicative formulation is used. *Electricity Bill Relative to Income*, *Effect of Information*, *Environmentally Responsible Behavior*, and *Experienced Value of Electricity* are thought independent of each other, however, the combined effects of these factors depend on each other. For instance, if one has information about how to conserve electricity and environmental incentives, but lacks money, then that affects the strength of the overall effect multiplicatively.

$$DtCE = EBRtI \times EoI \times ERB \times EVoE \tag{5.1}$$

The exponents *Elasticity of DfEEA (EoDfEEA)* and *Elasticity of DfEEH (EoDfEEH)* determine how strong the effect of *Desire to Conserve Electricity (DtCE)* is on the *Demand for Energy Efficient Appliances (DfEEA)* and *Demand for Energy Efficient Housing (DfEEH)* respectively, see Eqs. (5.2) and (5.3).

The exponents can be estimated in the following way. To represent a 50% increase in *Demand for Energy Efficient Appliances (DfEEA)* when the *Desire to Conserve Electricity (DtCE)* doubles, set $EoDfEEA = log_2(1.5) \approx 0.58$. For a 10% increase for *Demand for Energy Efficient Housing (DfEEH)* when the *Desire to Conserve Electricity (DtCE)* doubles set $EoDfEEH = log_2(1.1) \approx 0.14$. For a more detailed mathematical explanation see [1, p.338 and p.507].

$$DfEEA = DtCE^{EoDfEEA} \tag{5.2}$$

$$DfEEH = DtCE^{EoDfEEH} \tag{5.3}$$

Eqs. (5.4) and (5.5) present the formulas for *Demand for Appliances (DfA)* and *Demand for Housing (DfH)*. Using the same analogy as previously the exponents for appliance and housing demand can be estimated. To represent a 7% decrease in *Demand for Appliances (DfA)* when the *Desire to Conserve Electricity (DtCE)* doubles, set $EoDfA = log_2(0.93) \approx -0.10$. For a 4% decrease for *Demand for Housing (DfH)* when the *Desire to Conserve Electricity (DtCE)* doubles set $EoDfH = log_2(0.96) \approx -0.06$.

$$DfA = DtCE^{EoDfA} \tag{5.4}$$

$$DfH = DtCE^{EoDfH} \tag{5.5}$$

5.3.4 Supply side: Price, Capacity and Production.

The supply side is kept relatively simple as the main focus is on the demand side. Vogstad [36] has modeled electricity production in the Nordic electricity markets quite comprehensively in his study. Vogstad's model has been used as a starting point of the supply side submodel. Electricity production is not the main topic in this study, but it is important to include some of the feedback loops from the production side to the model. The electricity price affects both demand and production in the long-term, and therefore the effect of the price to the capacity and the capacity to the price has been modeled here. Figure 5.11 presents the submodel of the electricity supply side.

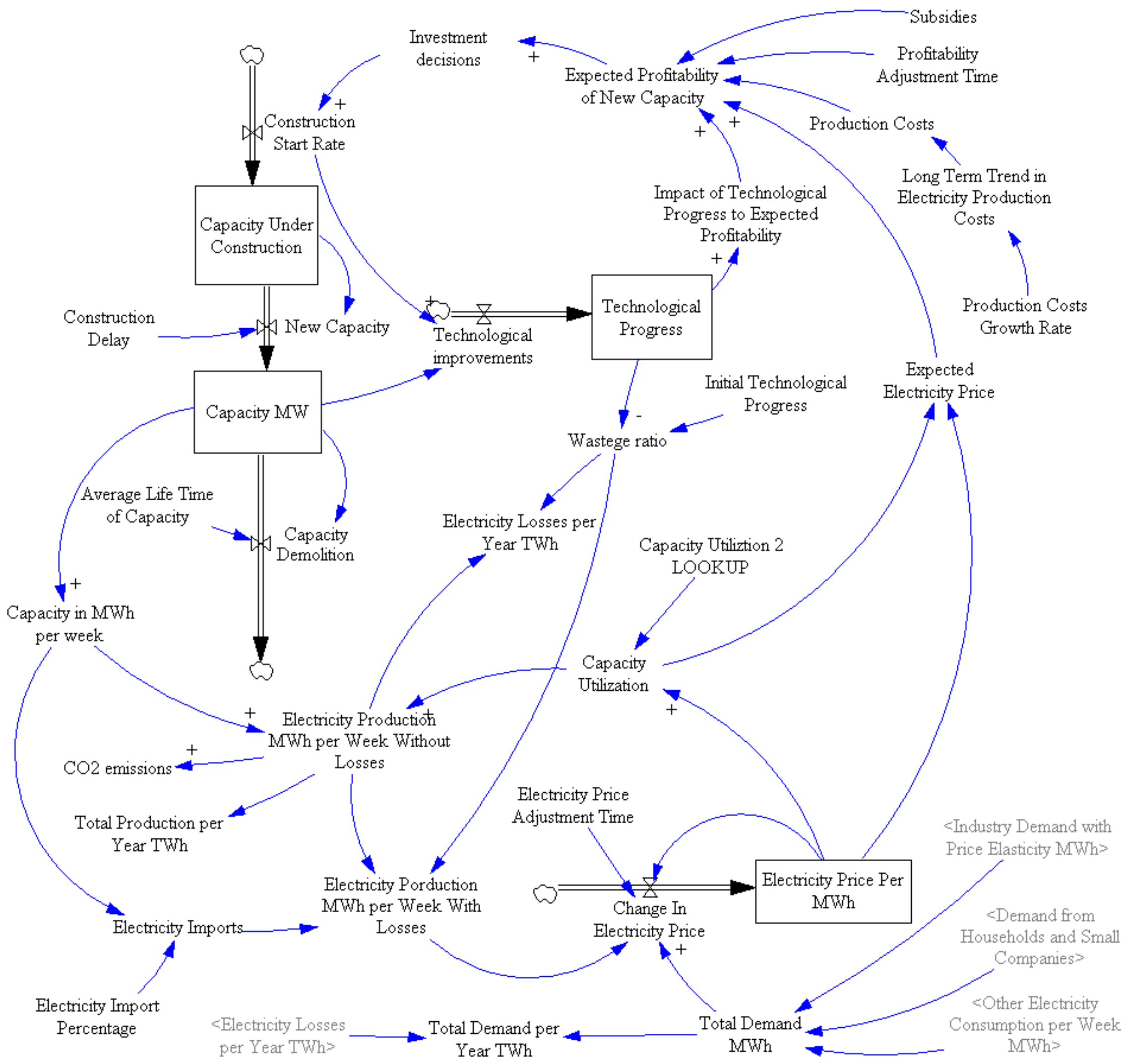


Figure 5.11: Capacity and production.

Important dynamics affecting the system in the long-term comes from the construction of new capacity. As seen in the model, when new capacity is decided to be built, it enters the *Capacity under Construction* stock, and after the average construction time it enters the *Capacity* stock. Construction delay can be something between two and ten years depending on the project. The new nuclear power plant decision, for instance, already came in 2001, and the plant is still under construction, with the estimated completion time at the moment being in 2014 [47]. This is a major feedback loop with significant delay, thus producing oscillation to the capacity and price.

Simulations revealed that the feedback from household consumption to the electricity price is relatively mild, and therefore, for the sake of simplicity, the supply side is excluded from the model analysis. Instead, a simple exponential growth model is used, see Figure 5.12. However, it is worth mentioning that this does not mean that the household consumption is not affecting the electricity price. The model lacks the feedback loop from the short-term model, i.e. from load profiles, to the long-term model. Even though household consumption is roughly a quarter of the total consumption of Finland, the impact on the price is probably more significant, because of peak demand. The model is not capable of taking into consideration the effect of load profiles to the electricity price; this requires further research.

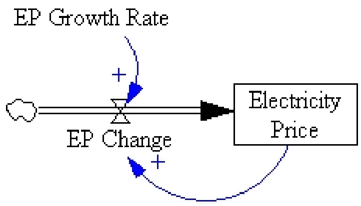


Figure 5.12: Electricity price.

5.3.5 Hybrid and Electric Vehicles

Figure 5.13 presents the submodel describing hybrid and electric vechichle (HEV) electricity consumption. This submodel is created because of the huge impact HEVs can have on the electrical grid in the long run. This is also an example of how different submodels can be added to the model without a feedback loop from other parts of the model. This could also be replaced by existing scenarios, but including this enables testing how the total consumption will change with different assumptions together with other parts of the model.

Two parameters are given to the model user, the starting year of HEV boom and the contact rate, which describes how fast HEVs will become dominant. The model is fit to follow the base scenario given by Ruska *et al.* [14]. The model is a modification of a Bass diffusion model [48] [1, pp.332-347] and research of Struben and Sterman [49] is used as a reference. This is a simplified model and the word of mouth is used as the dominant propagation cause; vehicle features, advertising, subsidies etc. are excluded.

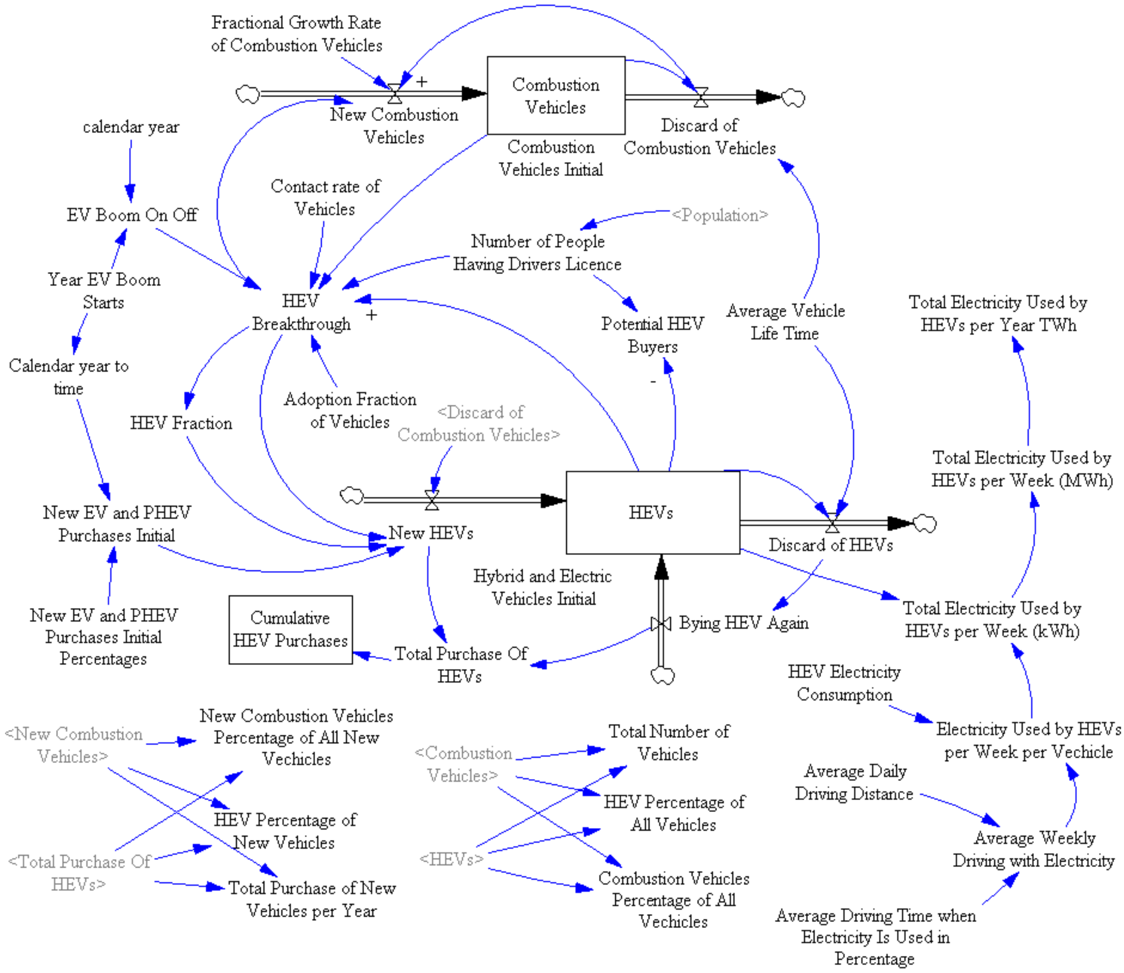


Figure 5.13: Hybrid and electric vehicles.

5.3.6 Propagation of Smart Meters and the Effect of Information

Smart meters are currently being installed in Finnish households. When a household has a smart meter, they can start using the services provided by the electricity companies (if there already are existing services). The adoption of AMR-services, presented in Figure 5.14, is modeled using two modified Bass diffusion models [48] [1, pp.332-347]. A Bass model is used for both smart meter installations and for the propagation of AMR-services.

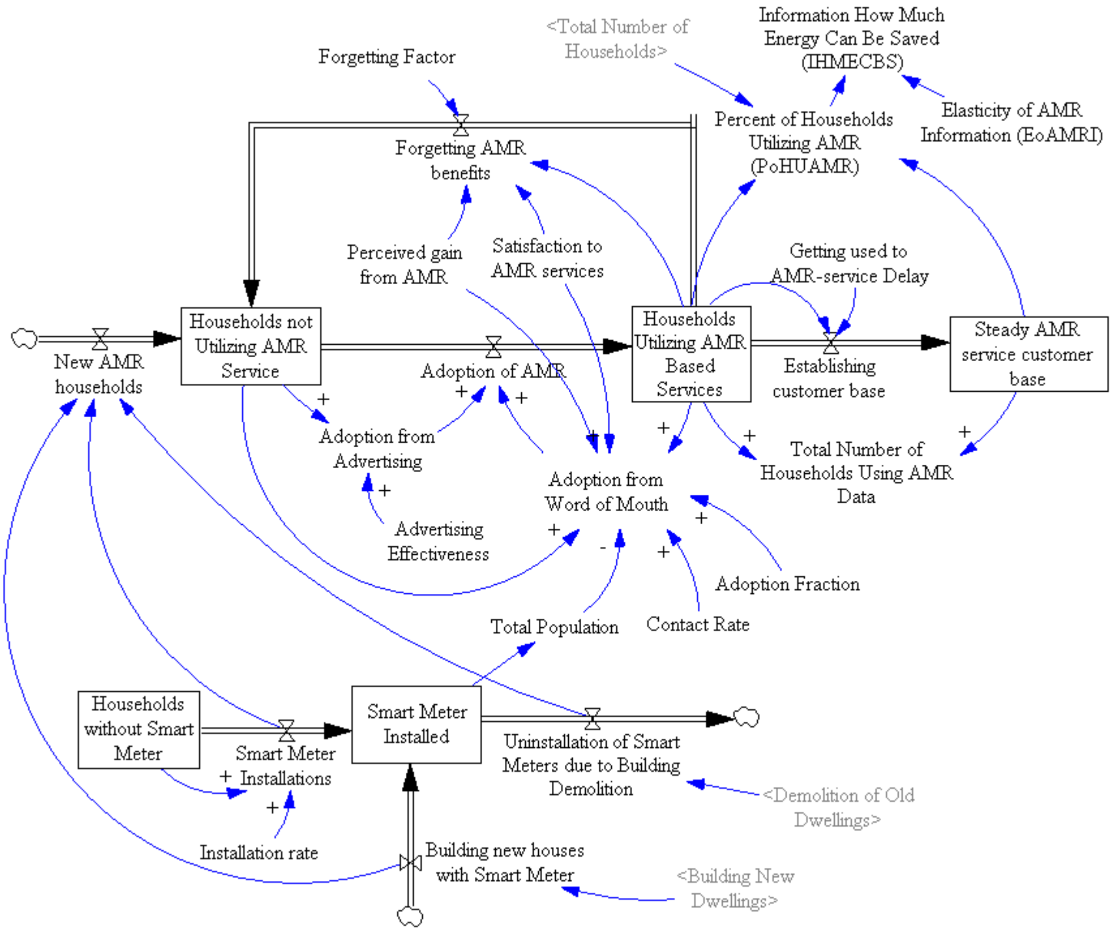


Figure 5.14: Smart meter and AMR-service propagation.

In a normal Bass model all adopters are spreading the word of mouth, but it is more likely in this case that after the purchase of a new service people spread the word a certain time and after a while their enthusiasm decreases and they are no longer spreading the word. This can be modeled by dividing adopters into two stocks, new adopters and former adopters. New adopters have just purchased the new service and they are spreading the word. Former adopters have purchased the service a while a go and they are no longer that excited about it.

Eq. (5.6) presents the formula for *Information How Much Energy Can Be Saved (IHMECBS)*, which depents on *Percent of Households Utilizing AMR (PoHUAMR)* and *Elasticity of AMR Information (EoAMRI)*. The exponent *Elasticity of AMR Information (EoAMRI)* determines how strong the effect of *Information How Much Energy Can Be Saved (IHMECBS)* is. This can be estimated in the same way as in the desire to conserve electricity. To represent 15% increase in *Information How Much Energy Can Be Saved (IHMECBS)* when the $1 + PoHUAMR$ doubles, set $EoAMRI = log_2(1.15) \approx 0.20$.

$$IHMECBS = (1 + PoHUAMR)^{EoAMRI} \tag{5.6}$$

In this model, an assumption is made that information has permanent effect on people's behavior. However, this is not necessarily true, Pihala [50] emphasizes that current studies have not yet confirmed this, hence future research is required.

5.3.7 Environmental Consciousness

Environmental consciousness is an interesting variable in the model. It affects the system in the long-term. Modeling environmental consciousness is not an easy task, nevertheless it is taken into account in some sense in the model as a scenario variable. The user can determine the growth rate of environmentally responsible behavior.

Figure 5.15 presents a sketch of the submodel describing environmental consciousness. This submodel is not included in the model, because the detailed model is not seen as important as other parts of the model and the model is kept as simple as possible. Nevertheless, this can be added to the model if needed.

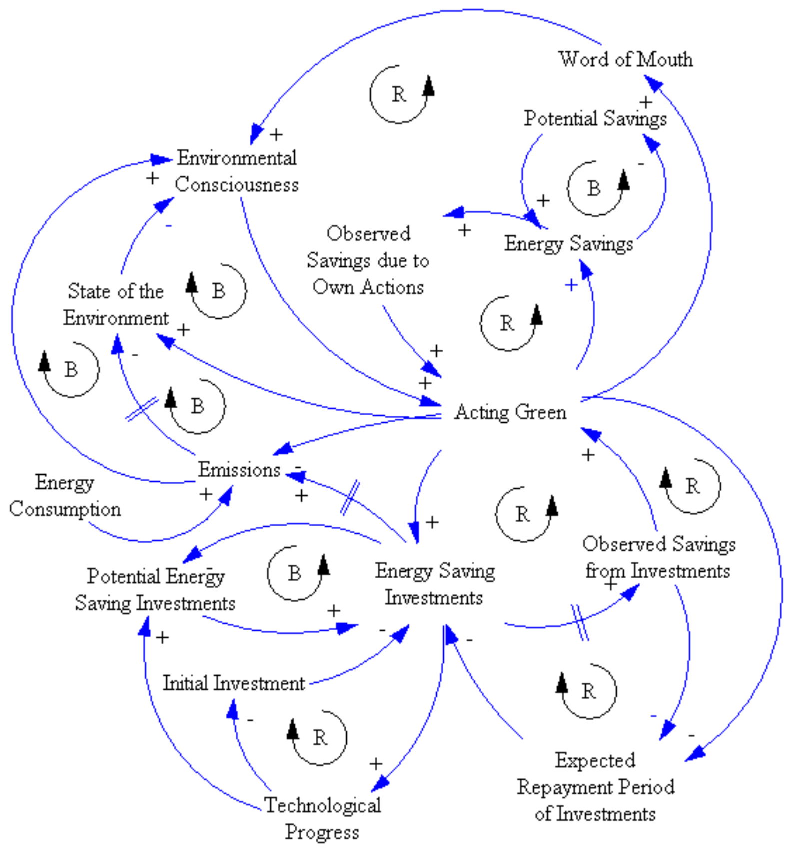


Figure 5.15: Environmental consciousness and acting green.

In Figure 5.15 environmental consciousness is divided into two variables, environmental consciousness and environmentally responsible behaviour, because people's consciousness can increase without them acting accordingly. Environmental consciousness is gained through education and time; this is a slow process. Environmentally responsible behaviour also depends on people's wealth. If people do not have money, they might not act environmentally consciously.

In this model, environmentally responsible behaviour affects both the decision whether to buy new appliances and the energy efficiency of the purchased appliances.

5.4 Testing and Validation

It should always kept in mind that all models are wrong or inadequate, although some models can be useful. In this chapter model assumptions are tested and flaws are tried to discover. The model is validated against historical data, and a comprehensive list of the validation results can be seen in Appendix A.

The model has been discussed with other researchers and the structure has been adjusted when flaws have been observed. The validation methods presented in Chapter 3 have been used in model validation throughout the modeling process.

Even if the model is capable of following historical data the model correctness is not yet proven. There is a possibility that the model explains the history without catching the process behind the data. If the model is not "predicting" the history, then the assumptions must be adjusted according to available information or the model should be rejected. It is important to understand that fitting the model to follow historical data does not mean that the model is correct. It only means that we cannot reject the model based on historical data, since history data only reveals one possible path among others. This is why other validation methods are needed.

A large amount of historical data is used in the model validation. The data has been collected mostly from the literature and from Statistics Finland (Tilastokeskus). Dwelling stock and the changes in the dwelling stock have been fitted using the studies by Pesola *et al.* [51] and by Lehtinen *et al.* [52]. Dwelling energy consumption has been derived from a study of Laitinen [53]. Data from Statistics Finland has been used in many parts of the model. Most useful reports have been the following: Asunnot ja asuinolot 2010 [54], Rakennus ja asunnontuotanto 2011 [55], Korjausrakentaminen 2010 [56], Väestöennuste 2009-2060 [57], and Ajankäyttötutkimus 2009 [58]. A report by Koreneff *et al.* [59] has been used to fit the overall consumption of households, industry, and services. Household appliance energy consumption data has been gathered from different sources, the most useful have been Adado [46] and Korhonen *et al.* [60]. Household lighting scenarios have been derived from a study of Sarvaranta [61] and Korhonen *et al.* [60]. Data on electricity prices, production, and capacity have been gathered from Nord Pool official website [6] and from the Finnish Energy Market Authority [4]. Data on the propagation of ground source heat pumps has been derived from Finnish heat pump association (Sulpu ry) [62] and data on the efficiency of heat pumps has been derived from [62] and [20].

5.4.1 Validation Simulations

The following figures present validation results against historical data. Data has been gathered from literature, as described earlier, and validation has been done against all found data. The behavior of several other variables have also been validated against historical data, for example: the percentage of households having different appliances, total electricity consumed by different appliance groups, number of dwellings, dwelling electricity consumption, average floor areas, GSHP purchases etc.

Figure 5.16 presents how households are divided between building types. Historical data is from Statistics Finland [54].

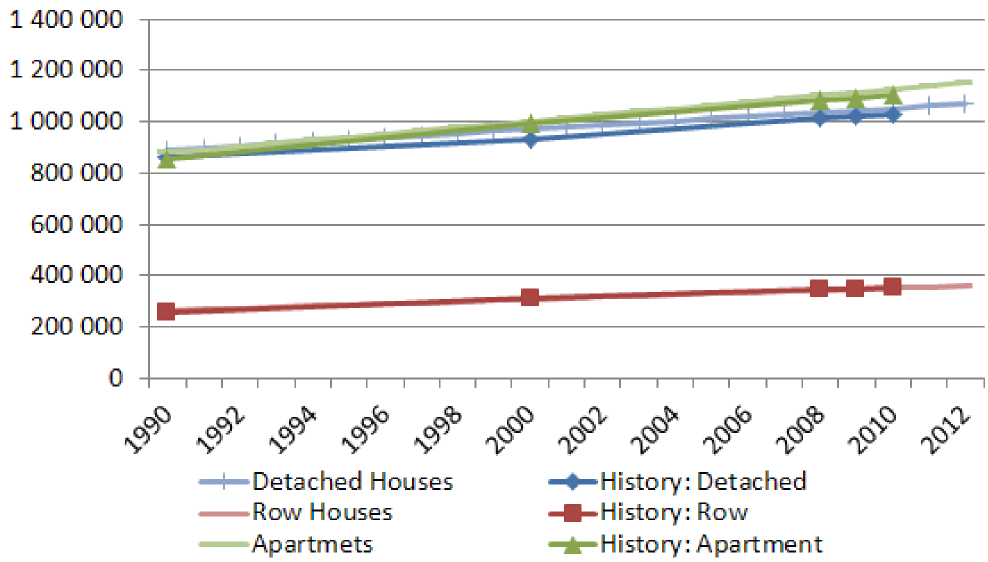


Figure 5.16: Number of households per building type: Detached houses, row houses, and apartmets.

Figure 5.17 presents the electricity consumption for laundry. Historical data is from the Adato-report [46].

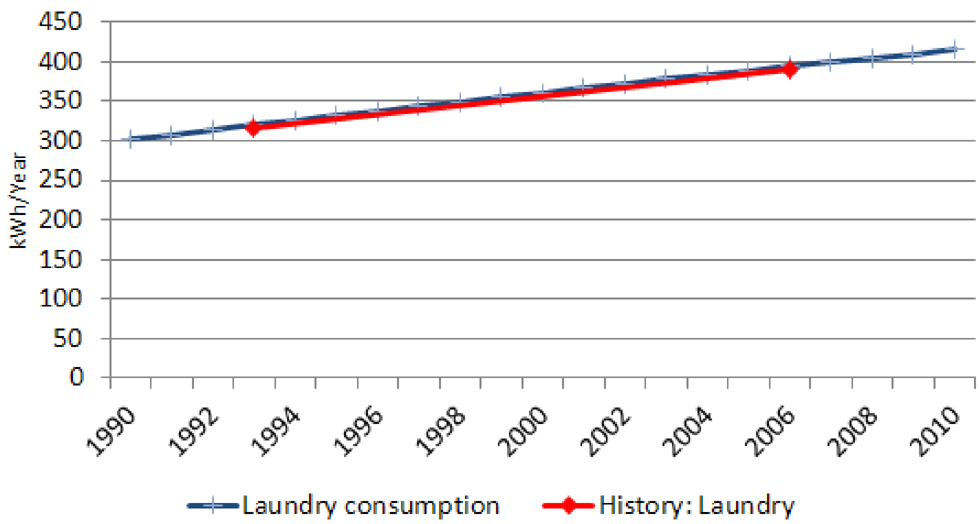


Figure 5.17: Average electricity consumption for laundry.

Figure 5.18 presents the GSHP installations given by the model. Historical data is from Sulpu [62].

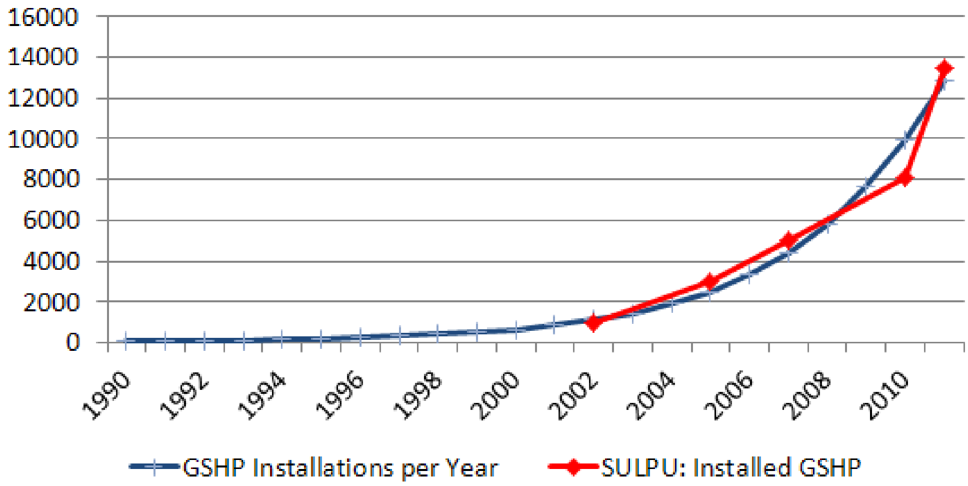


Figure 5.18: GSHP installations. Historical data from Sulpu Ry [62].

5.4.2 Sensitivity Simulations and Variable Analysis

With sensitivity simulations, the model robustness to parameter changes can be studied. Also several variables are examined more carefully. In sensitivity simulations, the results are shown with confidence intervals, e.g. 50%, 75%, 95%, and 100% of the trajectories being inside the shown area.

Effect of Price:

Figure 5.19 presents how varying the electricity price growth rate between 0 and 4% changes the electricity price. The growth rates presented in this thesis are always thought as real growth rates. The annual income growth rate is set at zero. The initial electricity price is set to 20€/MWh. With 4% growth rate, the price will be 216€/MWh in 2050, which means more than a tenfold increase.

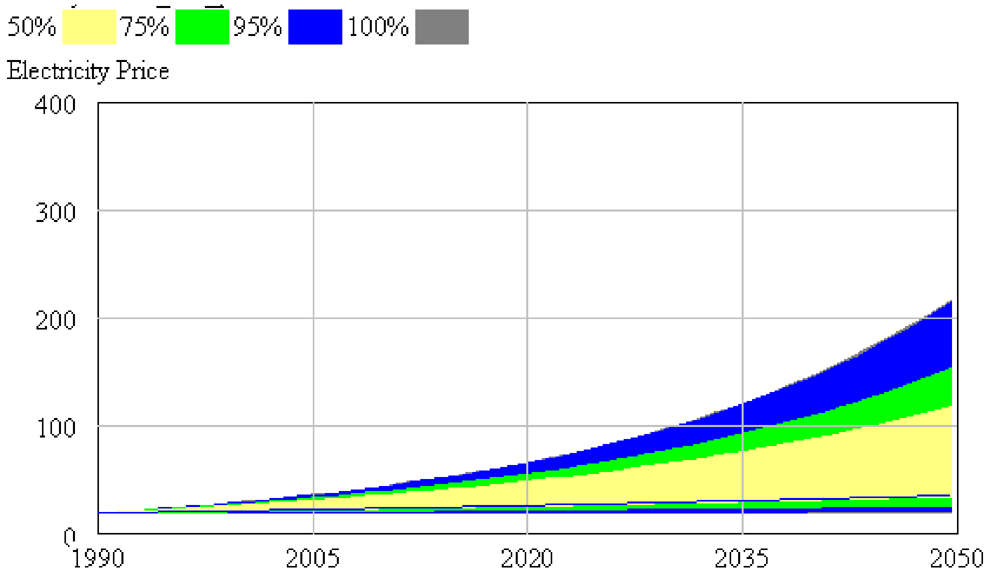


Figure 5.19: Sensitivity analysis: Electricity price (electricity price growth rate is varied between 0 and 4% per year).

As can be seen from Figure 5.20, the average money spent on electricity increases at maximum from 800€to 1700€, which is approximately a twofold increase. Also the electricity bill relative to income, Figure 5.21, is increasing at maximum twofold.

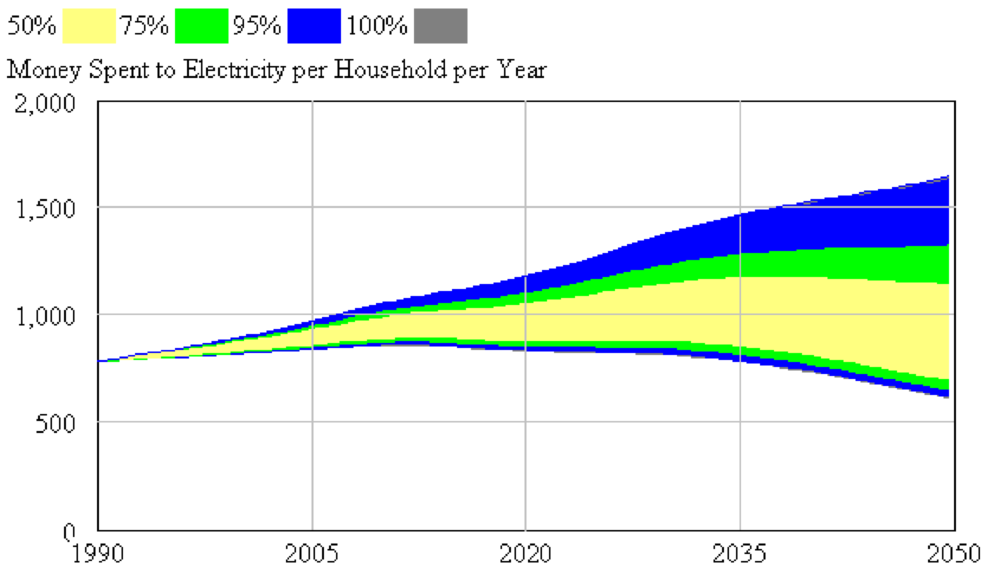


Figure 5.20: Sensitivity analysis: Money spent to electricity (electricity price growth rate is varied between 0 and 4% per year).

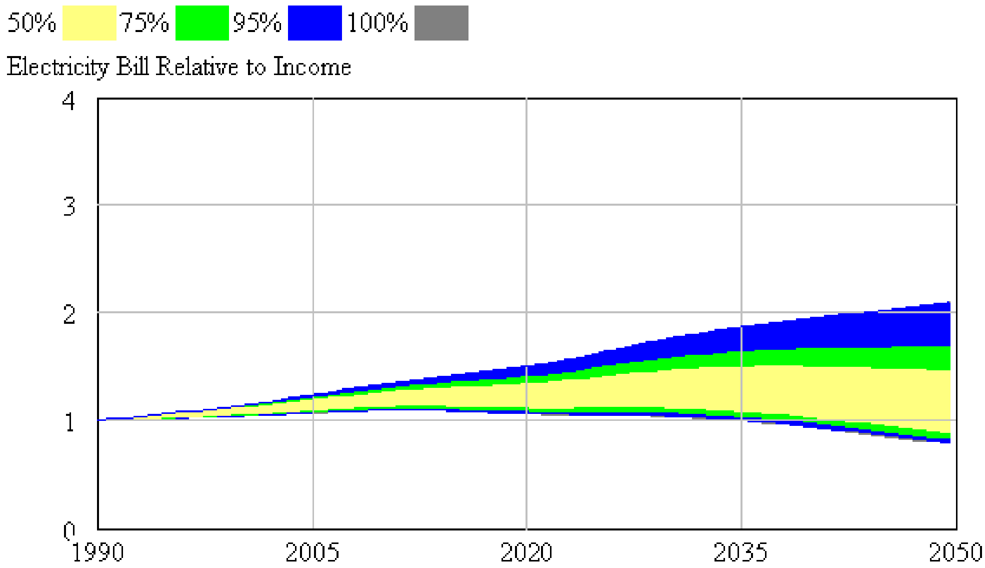


Figure 5.21: Sensitivity analysis: Electricity bill relative to income (electricity price growth rate is varied between 0 and 4% per year).

Figure 5.22 and Figure 5.23 present the effect of the varied electricity price on appliance and heating consumption respectively. As can be seen from the figures, there is roughly 10% difference in both appliance and heating consumptions.

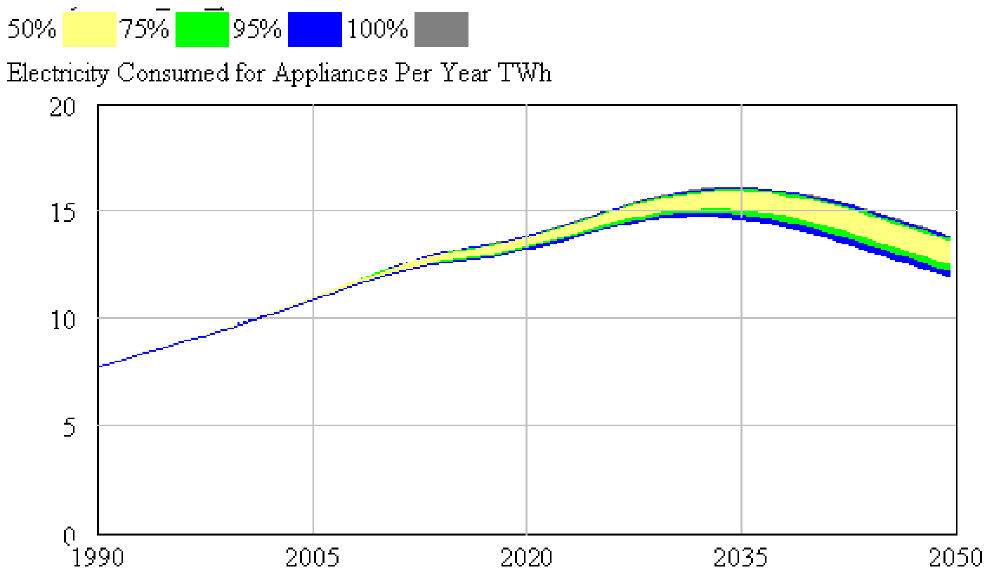


Figure 5.22: Sensitivity analysis: Household appliance electricity consumption (electricity price growth rate is varied between 0 and 4% per year).

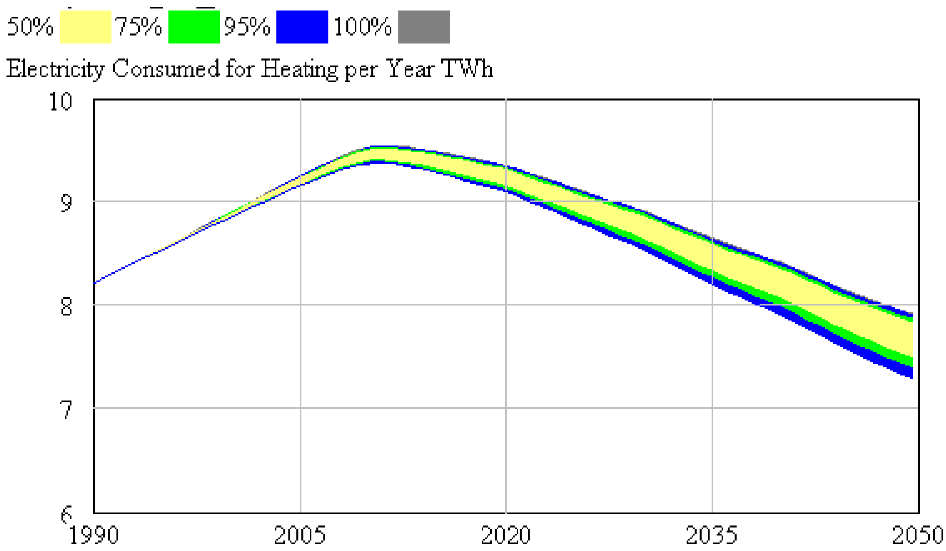


Figure 5.23: Sensitivity analysis: Household heating electricity consumption (electricity price growth rate is varied between 0 and 4% per year).

Heating methods:

There are several variables that clearly affect the household consumption more than others. For instance, ground source heat pumps have significant effect on heating electricity consumption. Figure 5.24 presents the future trends in detached house heating methods with a reference scenario by Laitinen [53]. Figure 5.25 presents the GSHP propagation scenario predicted by the model.

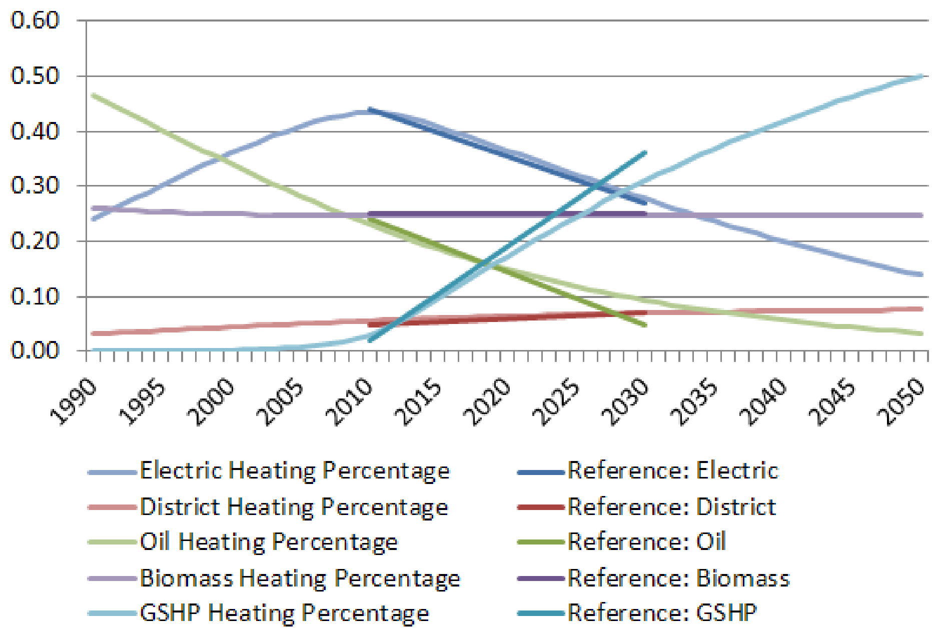


Figure 5.24: Detached house heating method proportions: electric, oil, district, biomass, and GSHP heating.

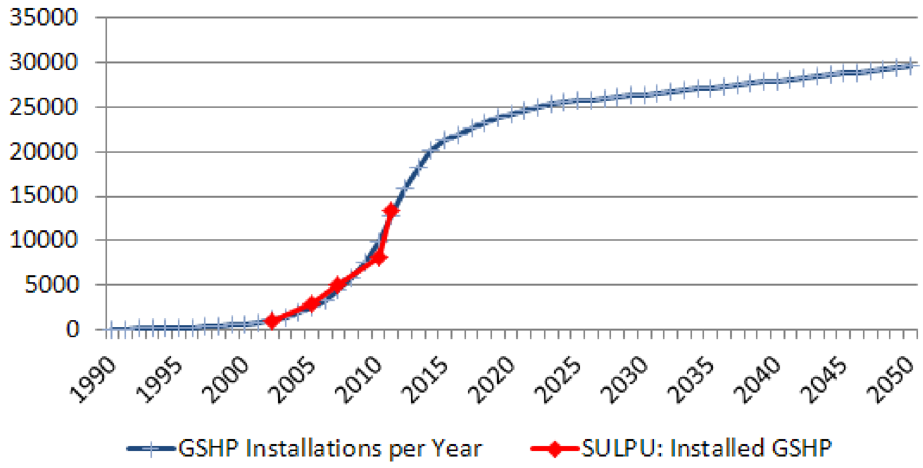


Figure 5.25: GSHP installations and historical values from Sulpu Ry [62].

As seen from the figures, the GSHP installations will change the heating method proportions. The propagation of GSHPs has a significant effect on heating electricity consumption, since GSHPs are replacing direct electric heating in households, thus the electricity consumption is decreased; The Enete-project [20] suggests that the true annual savings of GSHP are between 27% and 47%. This is one of the main reasons why household heating electricity consumption starts to decrease, and the turning point will be seen between 2012-2015.

Sensitivity analysis Figure 5.26 reveals how varying the annual savings of GSHPs electricity consumption between 25% and 47% affects the aggregated electricity consumption of households given that the GSHPs propagate as seen in Figure 5.25.

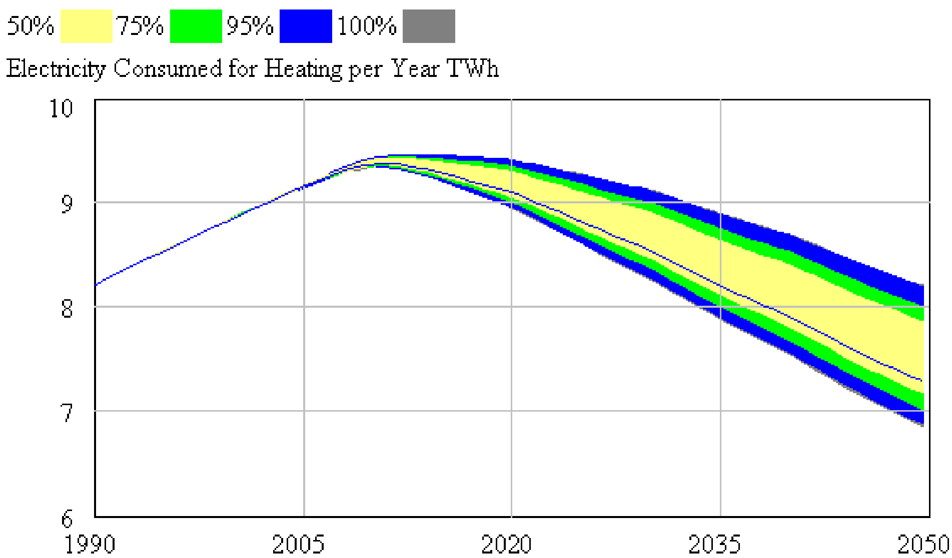


Figure 5.26: Sensitivity analysis: GSHP efficiency effect on electricity consumption.

Figures 5.27 and 5.28 present results related to Figure 5.26 with additional sensitivity simulations. Now also the adoption fractions of GSHPs, which describe the propagation rate, are varied, see Table 5.2. Lower adoption fractions are used to represent the effect of slower propagation; original values are the same the maximum values in the table. As seen in Figure 5.27, varying adoption fractions does not have significant effect on GSHPs propagation in long-term. As seen in Figure 5.28, in short-term, varying adoption fractions have minor effect on GSHP annual energy savings and in long-term the savings are not increasing. This is a result of the systems structure; even though the propagation starts slower, the positive feedback loop dominates the process and GSHP will eventually overtake the market of direct electric heating.

Table 5.2: GSHP adption fraction sensitivity parameters.

Parameter	**Min**	**Max**
GSHP adoption fraction (Detached house)	20	26
GSHP adoption fraction (Row house)	18	24

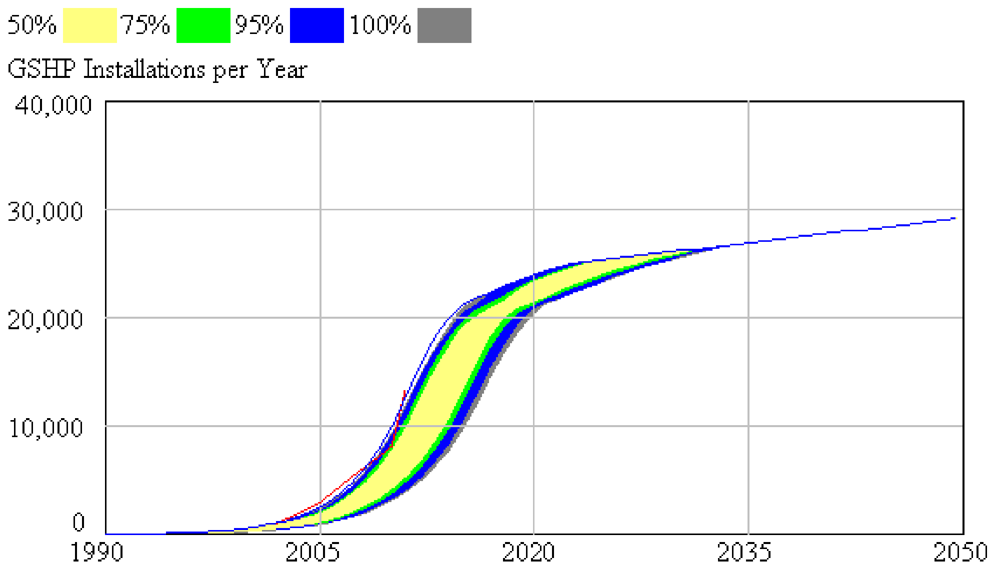


Figure 5.27: Sensitivity analysis: GSHP adoption fraction effect on GSHP installations.

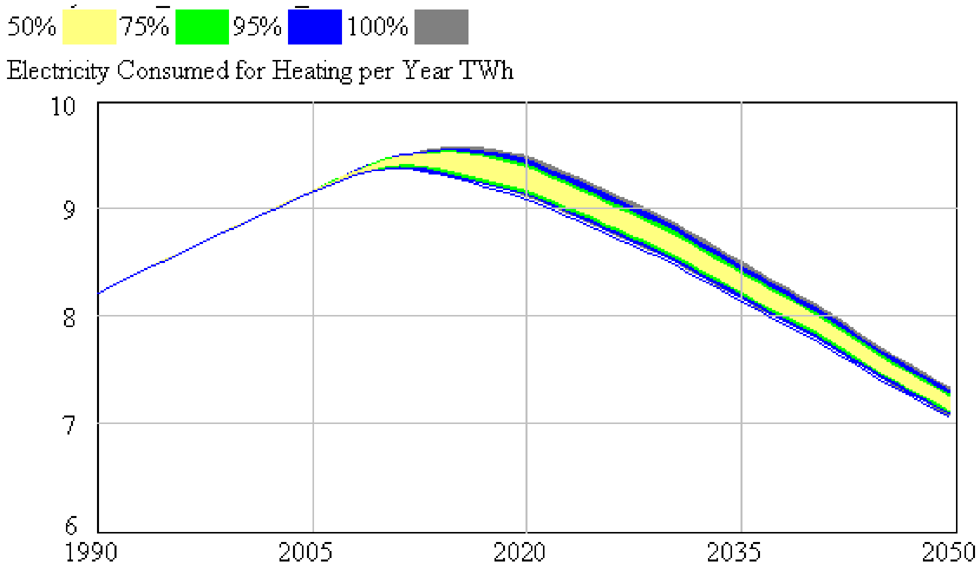


Figure 5.28: Sensitivity analysis: GSHP adoption fraction effect on electricity consumption.

5.5 Scenarios and Using the Model

In this section two different scenarios are discussed. First a base scenario is presented, which is fitted to follow scenarios found in the literature. Next a second scenario is presented with different assumptions, and then compared to the base scenario.

5.5.1 Base Scenario

Figure 5.29 presents simulation results. A reference case is derived from a report by the Ministry of the Environment [63]. The base scenario is a business as usual, BAU, case, where the ongoing trends of population growth, construction, and income are assumed to continue. Scenario S1 is generated using the most likely parameter values , e.g. energy saving policies, and it is fitted to roughly follow the reference scenario. Scenario S2 is the alternative scenario with different parameters; in this case the parameters are chosen to neglect most of the energy saving measures. Table 5.4 presents the altered parameter values. HEVs possible electricity consumption is also presented in the figure. The HEV scenario is fitted to roughly follow the scenario presented by Ruska *et al.* [14].

Table 5.4: Parameter values of scenarios S1 and S2.

Parameter	**S1**	**S2**	**Unit**	**Explanation**
Technology Adoption Rate	0.008	0.005		Appliance technologiacal development rate factor
Energy Policy 2012	10	0.0	%	Dwelling energy policy: decrease %
Energy Policy 2020	10	0.0	%	Dwelling energy policy: decrease %
Energy Policy 2030	10	0.0	%	Dwelling energy policy: decrease %
Energy Policy 2040	10	0.0	%	Dwelling energy policy: decrease %
GSHP Efficiency	60	70	%	GSHP energy consumption compared to direct electric heating

Energy policy 2012, *2020*, *2030*, *2040* are parameters, which the scenario analysis tool user can alter. They describe the dwelling energy consumption decreases. *GSHP Efficeincy* describes how much energy GSHP consumes on average compared to direct electric heating.

The difference between S1 and S2 is significant in 2050. **S1**: Appliances: 15.92 TWh, Heating: 8.08 TWh, and total: 24.00 TWh. **S2**: Appliances: 19.68 TWh, Heating: 10.77 TWh, and total: 30.45 TWh. Total difference is 6.45 TWh, which is roughly 7% of current electricity consumption. For comparison: the annual electricity generation of nuclear power units Olkiluoto 1 and 2 is roughly 7 TWh [47]. However, it should be kept in mind that scenarios ranging to 40 years ahead should be treated with caution.

Scenario S1 has a clear turning point in heating consumption in 2012; a turning point can also be seen in scenario S2, but the effect is not as strong. Occurrence of the turning point is due to the GSHP fast propagations which has already taken place, as discussed earlier, together with energy saving policies in the heating consumption of new dwellings. The turning point in the reference case is later, in 2020, than the model suggests. In scenario S2 the average efficiency of GSHP is assumed to be slightly lower than in S1; S2 also lacks other energy saving measures. In scenario S1 an assumption of 10% energy savings to new dwellings every decade is used. The long-term effect is significant, resulting in 2.69 TWh savings in 2050.

Appliance consumption scenarios are more difficult to generate. The difference in the scenarios is a result of the different technology adoption rate. In S1 the energy consumption of appliances is decreasing faster than in S2. The appliance consumption given by the scenarios stays almost the same until the year 2025, and after that the consumption starts to diverge rapidly.

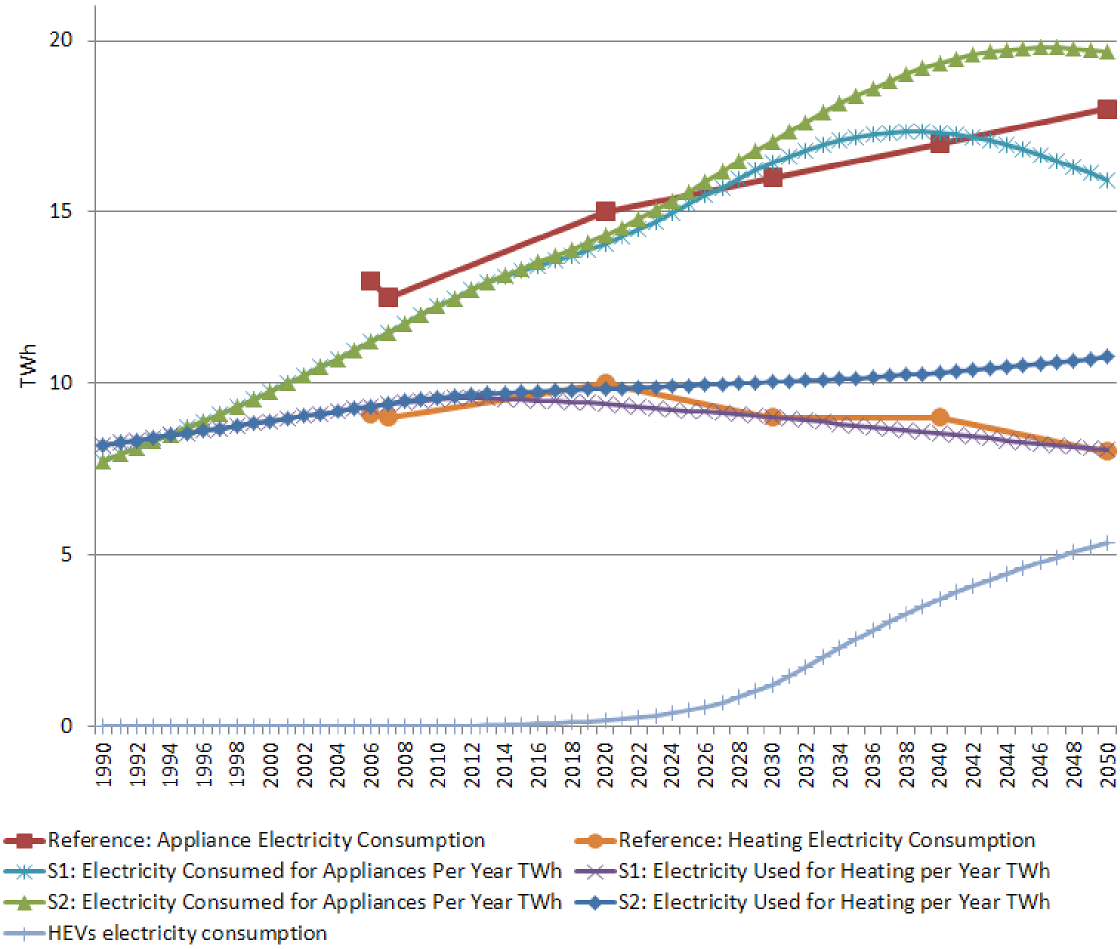


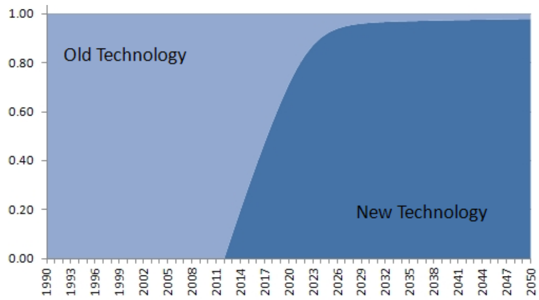
Figure 5.29: Total consumption of households: Scenarios 1, 2, and a reference case.

5.5.2 Other Scenarios

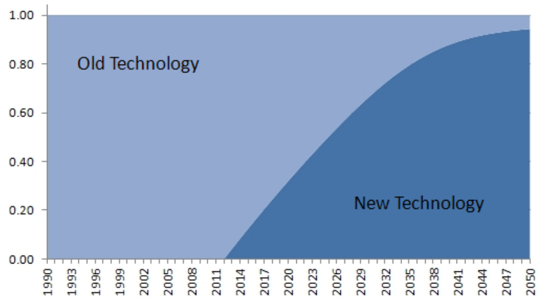
The scenario analysis tool user can test his/her own assumptions and compare them to the base scenario. Scenarios made in the model should always be compared to the base scenario and not thought as forecasts.

5.5.3 Propagation of Appliances

Figure 5.30 presents how fast new technologies, e.g. the smart grid enabled technologies, can emerge in the very best case. Figure 5.30a presents the case of dishwashers and Figure 5.30b the case of HVAC-devices. In the maximum speed of propagation an assumption is made that all purchased appliances from a given moment are new technology appliances. In practice this is of course not the case, new technologies are emerging relatively slow in the beginning due to several reasons. For example, before new services for these new technologies are common they are not likely to propagate rapidly. The effect of circulation speed is very obvious here, as the average life time for a dishwasher is 12 years and for a HVAC-device 30 years. If a new technology is introduced now for all new HVAC-devices, it takes 13 years (not 15 years because of the HVAC-device -stock growth) before 50% of the HVAC-device -stock has the new technology. In reality the propagation of a new technology starts slowly, increases, and then saturates. This affects, for instance, the propagation of smart grid enabled solutions, e.g. the demand response.



(a) Dishwashing maximum speed of circulation



(b) HVAC (heating, ventilation, and air conditioning) maximum speed of circulation

Figure 5.30: Speed of circulation describes how fast new smart grid enabled technologies can emerge. The x-axis presents years and the y-axis proportions of all particular appliances.

5.6 Future Research

The model could be further developed, for instance, the electricity price is not compared to other energy sources, which limits the usage of the model. If the electricity price is increasing compared to other energy sources, e.g. oil or biomass, then electric heating would lose market share to other heating methods and vice versa.

Summer houses are left outside of the study, because it is assumed that they do not have a significant effect on the total electricity consumption. However, more research is needed and if required, they can be taken into consideration in the model.

Chapter 6

Short-term Electricity Consumption Model

This chapter presents the short-term model built in this thesis. Section 6.1 explains why the model is created and gives a short description of earlier research in this topic. Section 6.2 explains the structure of the model. Section 6.3 presents detailed description of the short-term model. Section 6.4 presents the ideas behind appliance usage probabilities. Section 6.5 explaines how the parameters are generated for different households. Section 6.6 explains the testing and validation of the model. Section 6.7 presents the simulation results. Section 6.8 discusses the development ideas of the model.

6.1 Introduction

The short-term household electricity model made in this thesis is a bottom-up approach describing how aggregated household appliance electricity consumption emerges. The short-term model is needed for load profile generation and to test the integrated model introduced in Chapter 7. The model is built using Apros modeling environment [64] and Microsoft Excel.

The model is composed of an Apros-model describing the appliances of a single household, to be used together with Excel. The model is simulated several times with different parameters in order to obtain the load profiles. The simulation horizon of the model is one year, and the time resolution is 15 minutes. Therefore the model is capable of generating daily, weekly, monthly, and annual load profiles. The model does not describe long-term change in electricity consumption.

Household electricity consumption can be divided into household appliances and heating (and cooling) devices. This short-term model concentrates on district heated households, therefore excluding electric heating. The electricity consumption of appliances is divided into smaller segments, e.g. lighting, cooking, entertainment. The main idea is that if inhabitant is at home then appliances can be used. If no one is at home, then appliances are not used, except appliances that are on all the time, e.g. refrigeration devices. For every hour of the day probabilities are predefined for inhabitants being at home and for appliances being used.

Parameters are drawn from predetermined probability distributions.

Similar bottom-up approaches are found in the literature. Richardson *et al.* [65] have chosen a very similar approach for his model. Although even higher time resolution are advocated, i.e. 1 minute; the 15-minute time interval is chosen for this model. Richardson *et al.* have also seen the need to introduce daily probability profiles for every appliance group although the probabilities are determined slightly differently. Also Paatero *et al.* [66], Capasso *et al.* [67], Seppälä [39], Armstrong *et al.* [68], and Widen *et al.* [69] have done similar models.

In this thesis, the household electricity consumption model is used as a tool for illustrating the method of using top-down and bottom-up simulation models together. The calibration and validation of this short-term model is left for future research although calibration and validation methods are discussed.

Earlier research has usually concentrated on simulating current load profiles. However, the purpose of this model is to generate future load profiles. The model can be used alone to generate current load profiles, but the true benefit is gained when integrated into the long-term model, which enables simulating the evolution of load profiles over time.

A large amount of AMR-data is available for the model calibration and validation, and this has also affected the structure of the model. The calibration and validation process is difficult, and therefore it is wise to make it as easy as possible. This model differs from the other similar models because of the possibility to validate the model against the true statistical properties of household electricity consumption.

6.2 Structure of the Model

Figure 6.1 presents the general idea how the appliance electricity consumption is modeled. Apros-model describes a general household and it can be adjusted to describe any household using different parameters. Simulating a single household several times gives the advantage of studying the behavior of a single household and the aggregated effect of several households.

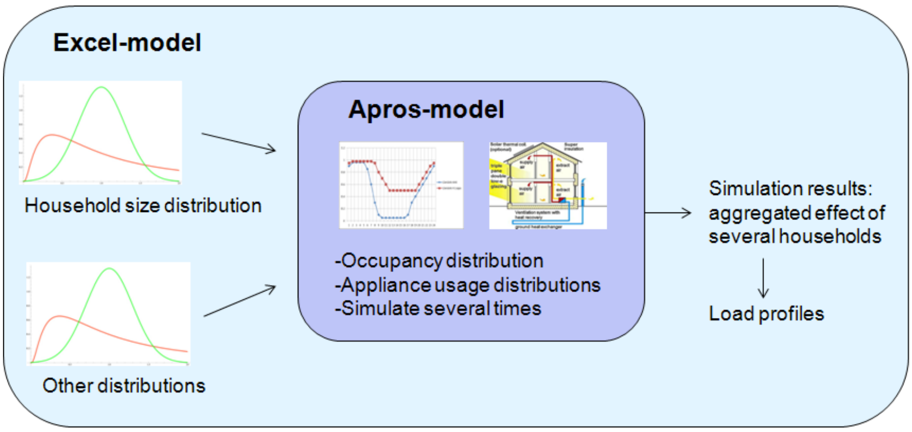


Figure 6.1: General description of the short-term model.

In the Apros-model time resolution is set to 15 minutes. This enables changes in the consumption at a given hour without increasing the simulation time of the model to an undesired level.

In Excel, needed distributions are determined. For instance, the household size distribution determines household sizes, which are used to determine other things in the model, e.g. lighting consumption. This way a comprehensive sample of households is selected.

6.3 Detailed Description of the Model

The model describes the electricity consumption of household appliances. Household appliances are divided into subgroups: lighting, sauna, car heating, entertainment, laundry, refrigeration, cooking, floor heating, HVAC (heating, ventilation, and air conditioning), and other appliances. These categories serve the purpose of modeling the change in load profiles and they are also used in the long-term model.

The model is composed of the submodels of different appliance groups. Figure 6.2 presents the entertainment appliance submodel. In the model the probability that an appliance is on comes from the left border. *External automation* -block gives out a uniform random variable between 0 and 1. If the random variable is below the defined probability, then the appliance is turned on. In the picture the random variable is 0.2934 and the defined probability is 0.099, which means that the appliance is not turned on. If the appliance is turned on, then, in this case, the appliance is running 3600 seconds. This is based on the assumption that an appliance is usually on a given time rather than switching on and off continuously dependent on the random variable. A laundry machine, for instance, is usually on roughly two hours. After deciding if the appliance is on it will be multiplied by *House occupants*, which is 0 or 1. This means that appliances can be on only if someone is at home. This is of course not the case with refrigeration devices etc.

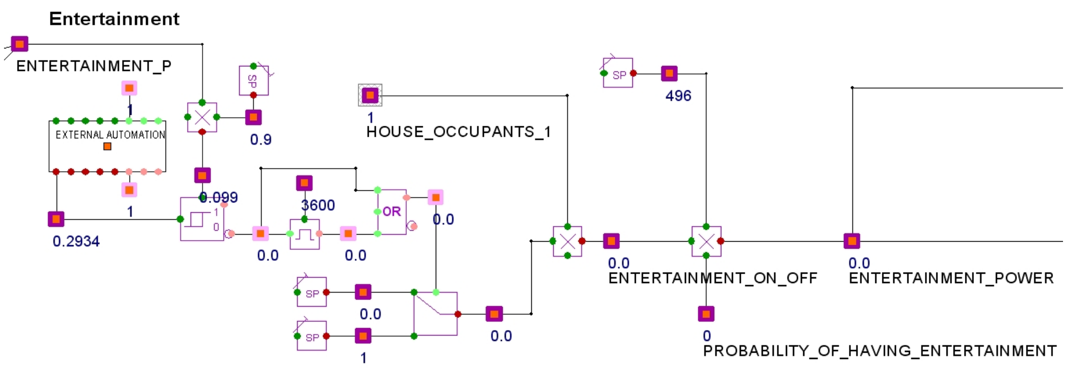


Figure 6.2: The short-term model - electricity consumption of entertainment appliances.

It is easy to add additional conditions to the model if required. In the car heating submodel, for instance, the outdoor temperature is taken into consideration. People are using car heating, if the outdoor temperature is below a certain temperature, e.g. five degrees.

Solar radiation affects the use of lighting devices. In the Nordic countries this affects the electricity consumption, since the summer days are long and the winter days are short and lighting is needed more often.

There are many parameters in the model that can be adjusted, e.g. the power consumption of appliances, appliance average operating time at one instance of use (when an appliance is turned on, how long it will be used), the probability of having a certain appliance, appliance usage probabilities, etc.

The short-term model, part of it seen in Figure 6.2, describes a single household. In order to obtain load profiles the Apros-model needs to be simulated several times with different parameters. This is done using an Excel user interface. VBA-code generates the needed parameters for the simulations from the predetermined probability distributions, thus giving an extensive set of parameters. The model describing one household is made using the Apros modeling environment, and combined with Excel it describes a large set of households.

6.4 Appliance Usage Probabilities

Electricity consumption has been divided into smaller components, as described earlier. Appliances can be used when someone is at home. Household occupancy is modeled as a random variable, people are at home or they are not. Household occupancy at a certain time of the day follows a given probability distribution. This probability distribution is derived from automatic meter reading (AMR) data. Inhabitants and appliances are separated, because when modeling the future change in electricity consumption appliance usage probabilities might change, while inhabitant probability of being at home is not likely to change However, if inhabitant probability of being at home changes, the reasons behind the change are not the same than behind the change of the appliance usage probabilities. For example, if a new tariff structure is introduced, the appliance usage probabilities are changing but the probability of being at home is not. Figure 6.3 presents the idea behind the usage of probability distributions.

The probability of being at home is the most important probability distribution determined. Probability distributions describing appliance usage probabilities are conditional probabilities given that the inhabitant is at home. For every appliance group a probability distribution is determined, which determines the probability of turning an appliance on for every hour of the day. Another parameter defines how long the appliance is on. Weekdays and weekends are treated separately.

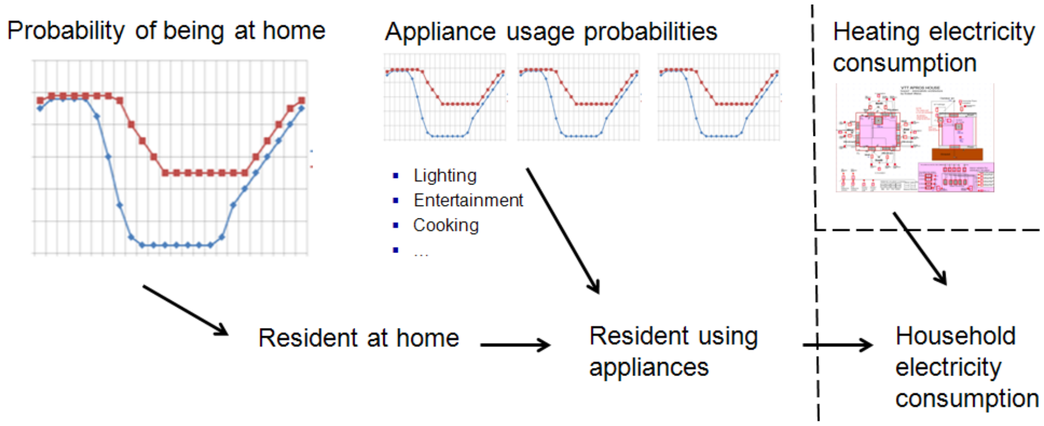


Figure 6.3: General description how the short-term model is divided into submodels.

Conditional probabilities and the Bayes theorem give: Eqs. (6.1), (6.2), and (6.3).

$$A := \begin{cases} 1: & \text{Appliance on} \\ 0: & \text{Appliance off} \end{cases} \tag{6.1}$$

$$B := \begin{cases} 1: & \text{Inhabitant at home} \\ 0: & \text{Inhabitant not at home} \end{cases} \tag{6.2}$$

$$P(A=1|B=1) = \frac{P(B=1|A=1)P(A=1)}{P(B=1)} \tag{6.3}$$

Using the law of total probability gives: Eq. (6.4)

$$P(A=1|B=1) = \frac{P(B=1|A=1)P(A=1)}{P(B=|A=1)P(A=1)+P(B=1|A=0)P(A=0)} \tag{6.4}$$

$P(A)$ is the probability of using an appliance, i.e. $P(A)$ is the probability of using the appliance regardless of anyone being at home. This is difficult to measure without test houses. $P(A|B)$ means the conditional probability of using an appliance given that someone is at home. On the other hand, this is also difficult to measure with test households, because it is hard to say if anyone is at home when the appliance is on. However, the conditional probabilities could be constructed by experts or by a survey. Separating the probability of being at home and the appliance probabilities also make it easier to consider different population groups, because using conditional probabilities it is enough to change only the probability of being at home. Also $P(A=1)$ (appliance is on) is easier to measure than $P(A=1|B=1)$ (appliance is on given that someone is at home), since literature already gives estimates of how many hours people are using different appliances per day and per week.

In most cases $P(B=1|A=1)=1$, when assumed that a device is off if no one is at home, although this is not true in all cases. However, this simplifies the equation, see Eq. (6.5). This knowledge can be used when determining the probability distributions.

$$P(A = 1|B = 1) = \frac{P(A = 1)}{P(B = 1)} \tag{6.5}$$

The usage probability distributions are presented in the appendix. If there is nothing that can be said about the shape of the probability distribution, then a uniform distribution is used, which means that no information about the particular phenomenon is available.

6.5 Parameter Generation for Different Households

The Apros-model needs to be simulated several times in order to obtain the load profiles. As mentioned earlier, every household simulated should be somewhat different. Distributions are used in order to obtain a comprehensive sample of households of a different kind. Parameters are obtained by drawing random variables from predetermined probability distributions describing variables. Household floor area for a single household, for instance, can be randomly drawn from household floor area distribution. Furthermore, household equipment level can be decided based on household floor area, also using distributions.

The same approach can be used to decide whether the household is a detached house, a row house, or an apartment and then choose the floor area from the floor area distribution. Detached houses are larger than apartments. The same approach can be used to determine the number of occupants, the probability of having an appliance, etc.

6.6 Model Calibration and Validation

Model validation is an important part of modeling. As mentioned in previous chapters, a model cannot be proved to be true, because all models are approximations of reality. However, the model can be falsified or its structure and behavior can be validated against real data and expert evaluations, and thus conclusions on the usefulness of the model can be made.

There are several ways to test the model. The easiest way is to compare the simulation results with the results found in the literature. Several studies give valuable information on the household electricity consumption. For example, average appliance usage times can easily be compared. Also the simulation results can be compared to the load profiles found in the literature. A more sophisticated method is to study the distributions of electricity consumption. This includes studying the AMR-data. However, a comprehensive validation of the model is not in the scope of this thesis, only validation ideas are presented for future research.

Data from several studies has been used to calibrate the model, even though the model is not yet ready. The Adato report [46] gives lots of insightful knowledge about the household electricity consumption in Finland. The Adato report also gives information about how the electricity consumption habits have changed, because the same study was made in 1993 and in 2006.

How many hours/days/weeks an appliance is on during a given time is calculated in the model and compared to real data. Estimates how long different appliances are used can be found in [70].

AMR-data is used in the validation of the model. This is possible by using district heated households chosen from the AMR-data set. District heated households lack electric heating, and therefore their electricity consumption depends only on appliances.

6.6.1 Comparison of Existing Load Profiles

The model can be calibrated using existing information on the load profiles. Figure 6.4 presents data how electricity consumption in Swedish households [71] is divided between appliances and how the load profile arises from this data. This kind of data is compared to the data the short-term model is generating, and in the case of differences calibration is done. The advantage of this approach compared to the AMR-data is that this reveals how the load profile is composed of different appliance load profiles. This rough calibration is a good place to start.

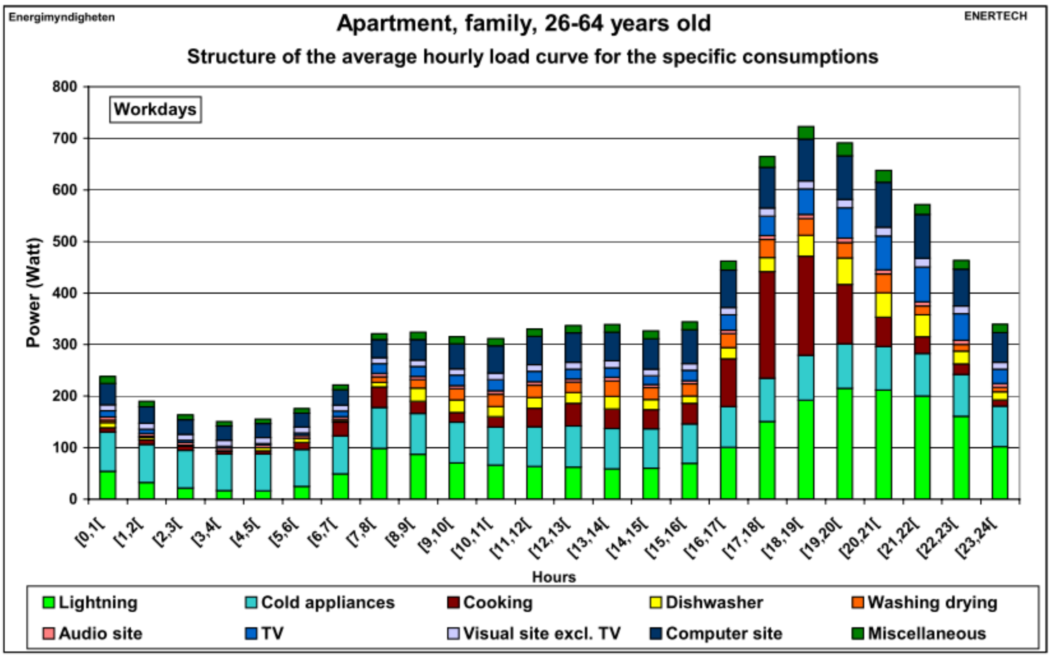


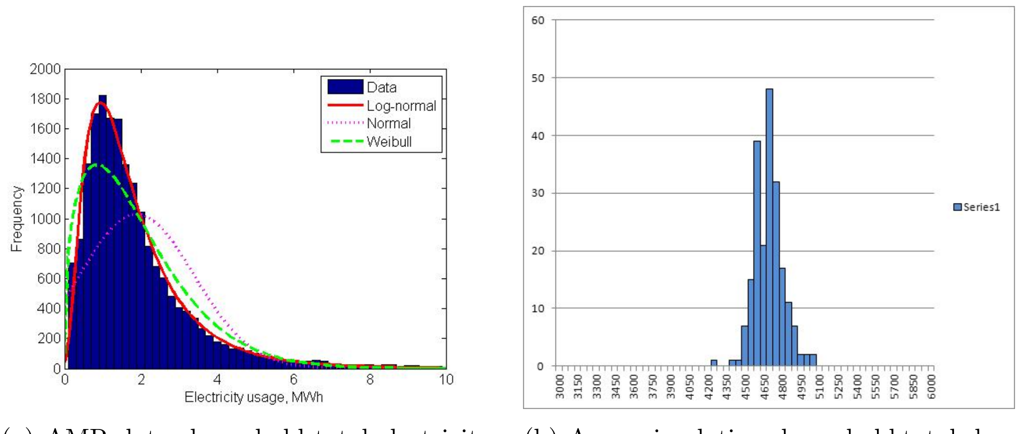
Figure 6.4: Load profile of an apartment: family 26-64 years old, no electric heating, workday. [71]

6.6.2 Hourly and Annual Electricity Consumption Distributions

People consume different amounts of electricity at different times of the day. When studying the consumption of a single household, the consumption might seem quite random. However, when studying the statistical properties of the consumption, it can be seen that the consumption is distributed in a well-defined way. Zero consumption is rare, but also very large consumption is rare during a single hour. The upper limit of the consumption is the total electricity consumption capacity of one household and lower limit is zero, or in practice it is the standby consumption. The statistical properties of electricity consumption can be used in model calibration and validation. The simulation results should have the same statistical properties as the measured AMR-data has. If AMR-data and the model give different distributions or statistical indicators, then we can say that the model is not correct and improvements are required. If the model gives the same distribution as the AMR-data, then the model is in this sense correct.

Electricity consumption distributions were presented in Chapter 4, see Figure 4.2. Electricity consumption magnitudes are shown in the x-axis. The frequency of how often certain electricity consumption occurred is shown in the y-axis.

Some houses consume less energy than others. Household electricity consumption distributions are already discussed in Chapter 4. Figure 6.5 presents real total household electricity consumption in 2010 (shown in Chapter 4) and the short-term model output. This can also be used in model calibration in the same way that the hourly consumption data is used. The model should give a similar distribution. As seen in the figure, the distributions are clearly different, and therefore improvements are required in the model.



(a) AMR data: household total electricity consumption. [38]

(b) Apros simulation: household total electricity consumption. X-axis: electricity usage kWh, y-axis: frequency

Figure 6.5: AMR-data and simulation model distribution comparison.

6.7 Simulation Results

Figure 6.6 presents a simulation result of a single household. Even though the pattern seen in the figure is quite random, some regularities can already be seen. For instance, the consumption is low during the night and high during the day. Figure 6.7 presents the aggregated effect of several households, now the load profile is emerging and conclusions about the electricity consumption can be made.

To clarify the model structure: the Apros-model gives results like seen in Figure 6.6, as it is a model of a single household. The short-term model, which is created using the Apros-model and Excel, gives results seen in Figure 6.7, as a single household is simulated several times and the results are collected in Excel.

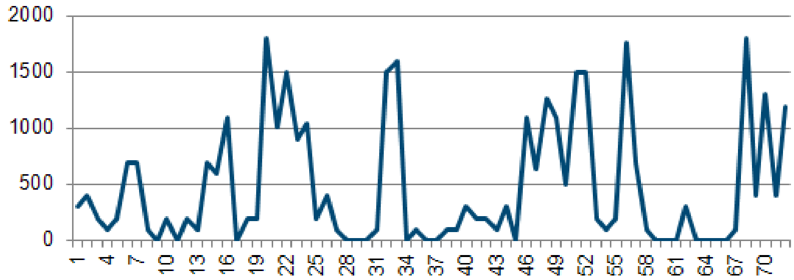


Figure 6.6: Simulation of one household.

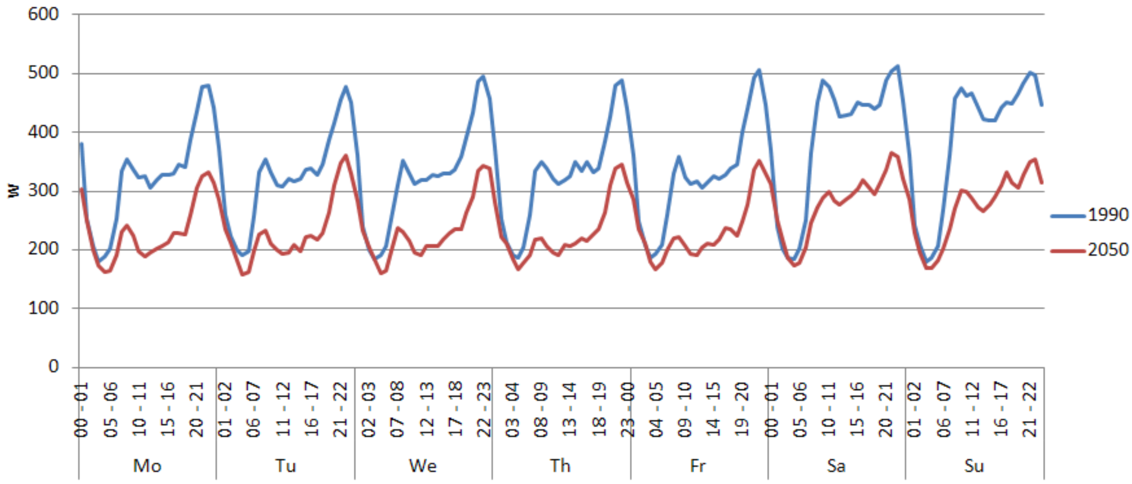


Figure 6.7: Simulation of several households: load profiles.

More simulation results of the short-term model are shown in the next chapter, showing the integration of the short- and long-term models.

6.8 Further Research

In this thesis, only a framework for the bottom-up electricity consumption model is implemented. Future research is required to complete the model and to calibrate and validate it.

The model could also be developed by introducing different population groups. Probability distribution for being at home could be defined for these population groups. Here are some suggestions for how residents could be segmented: nine-to-five workers, shift workers, night workers, senior citizens, unemployed, families with children, students, etc.

Chapter 7

Integration of the Models

The propagation of appliances, heat pumps, entertainment appliances, etc., is a complex process consisting of interaction of individuals. The shape of load profiles is an aggregated load of all households. However, the propagation of appliances is changing household consumption, and therefore a link between the consumer behavior and load profiles is required, which is established in this chapter.

This chapter presents a new approach, which enables simulating the evolution of load profiles over time. Section 7.1 explanes the purpose of the integrated model. Section 7.2 presents how the integration is implemented. Section 7.3 presents the simulation results. Section 7.4 discusses the future research required to be done.

7.1 Purpose of the Integrated Model

Many parties in the electricity markets, e.g. electricity suppliers and distributors, are interested in knowing how electricity load profiles are changing over time. System dynamics gives the long-term trends and the short-term model gives load profiles. By combining these two it is possible to simulate scenarios on how the load profiles change over time.

There are two reasons why two models were decided to be created in the first place. Use of different modeling techniques allow utilizing the best practises to given problems and no trade-offs are needed. Of course, if the models were created using only one modeling tool, then no integration would be needed. However, the main reason for two different models and integration is the large difference in time constants in the models. The time constant is short in the short-term model and long in the long-term model, this exposes the model to the problems of stiff systems. A system is said to be stiff when it has fast and slow dynamics. If the time constants related to fast and slow dynamics differ significantly from each other, then the ordinary numerical methods can fail and cause errors. The time step has to be small enough to capture the fast dynamics, but at the same time it can be too fast and corrupt the slow dynamics by round-off errors. [1, p.909]

7.2 Integration

7.2.1 Models made in this thesis

Table 7.1 presents a summary of the key points of the models created in this thesis.

Table 7.1: Summary of the models

The Short-term Model	The Long-term Model
Bottom-up -approach	Top-down -approach
Time horizon: one year	Time horizon: 40 years
Resolution: hours	Resolution: weeks
Household appliance usage	Dynamic long-term phenomenon
Load profiles	Change in total electricity consumption
Uses data from the long-term model	Produces data for the short-term model
Validation against AMR-data	Validation against historical data
Individual households	and expert evaluations
and aggregated effects	Consumer behavior
	Political decision making
	Scenario analysis tool

7.2.2 Integrated Model Implementation and Usage

Integration is implemented using Microsoft Excel and Visual Basic for Applications (VBA). The created Excel user interface is communicating with both Vensim and Apros programs.

The long-term model is simulated first and then the defined parameters are transferred to the short-term model, which is simulated using Excel and Apros. In Excel the parameters for the short-term model, i.e. for every household, are determined. In Apros the households are simulated with given parameters. After the simulations, the data is imported back to Excel where the results can be processed.

7.2.3 Data Transferred Between the Models

The long-term model gives long-term trends, e.g. how the number of households, the number of appliances, energy efficiency, population, and total electricity consumption are evolving over time. These variables are transferred into the short-term model.

7.3 Simulation Results

Chapters 5 and 6 already presented the simulation results of the individual models. In this section results of the integrated model are presented.

The total electricity consumption is not the only thing affecting the load profiles. Figure 7.1 presents how the relative proportions of appliances change over time. This affects significantly the load profiles, since appliances have different power consumption and are used at different times of the day.

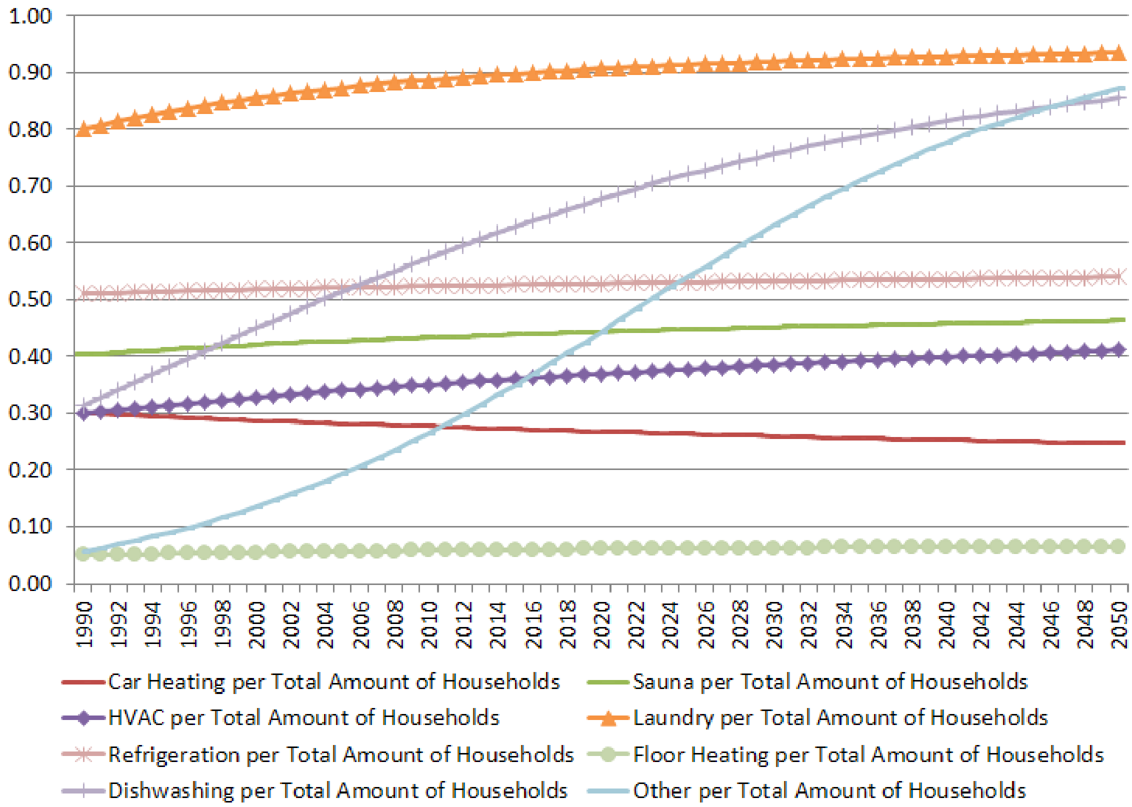


Figure 7.1: Appliances relative to the amount of households.

Figure 7.2 shows how the appliance average power consumptions changes over time. This affects significantly the load profiles. For instance, the lighting power decrease is one of the major reasons for the change in the load profiles. The average power of appliances describes the energy efficiency of appliances. Other factors affecting electricity consumption, such as appliance operation times, are treated separately.

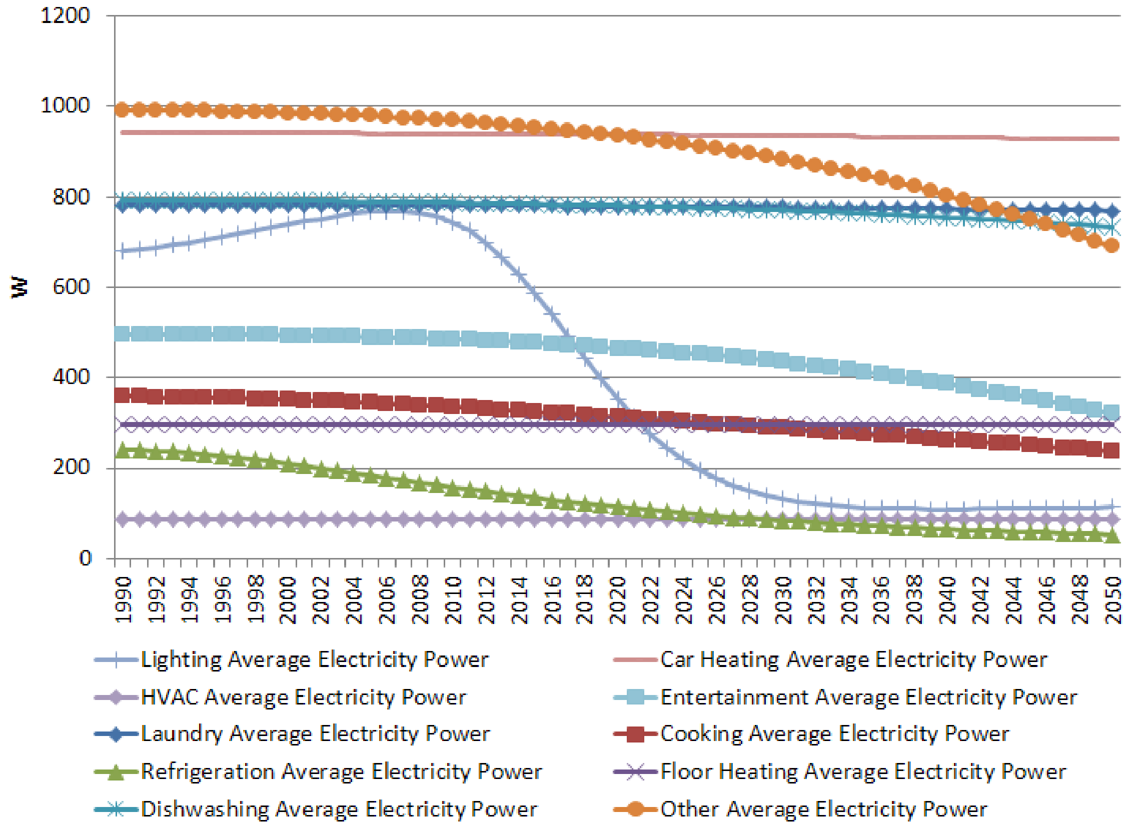


Figure 7.2: Appliance average power.

The results presented in Figures 7.3, 7.4, and 7.5 are only sketches, since the short-term model is not yet calibrated. However, preliminary conclusions can be made and the usefulness of the modeling method can be evaluated.

Figures 7.3 and 7.4 present daily and Figure 7.5 presents weekly load profiles generated using the integrated model. As explained earlier, first the long-term model is simulated and the required variable values from the given time instance are transferred to the short-term model, which generates the load profiles. Figure 7.6 presents the load profiles derived from AMR-data.

As can be seen in the figures, there is a large difference between the load profiles in 1990 and 2050. This is a result of different amounts of appliances and change in appliance energy efficiency. For instance, in 1990 most of the lighting devices used are incandescent bulbs whereas in 2050 mostly energy efficient lighting equipments, such as LEDs, are used. This change affects both the total consumption and the load profiles. In 1990, the consumption was significantly lower during the night than the day. When investigating the situation in 2050, this has changed, the consumption during the night is still lower than the day, but the difference is not as large as it was. The major reason for this is the change in lighting equipment energy efficiency, as seen in Figure 7.2.

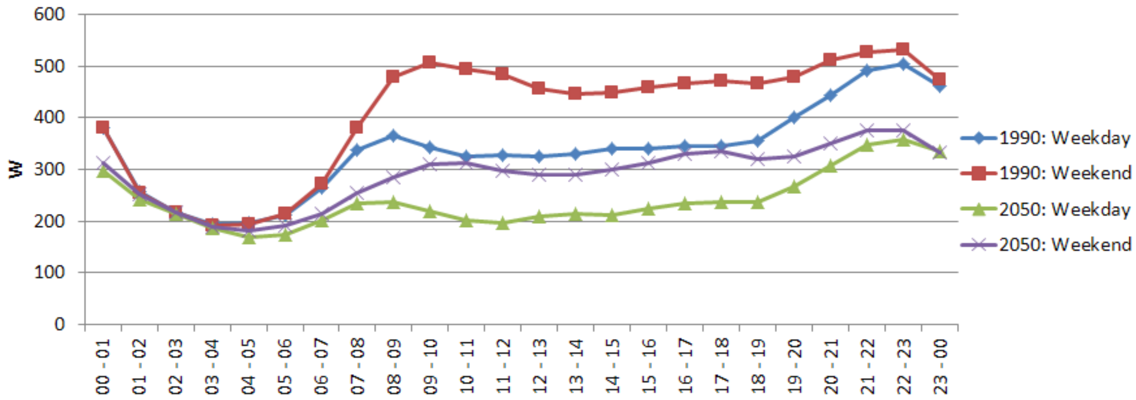


Figure 7.3: Daily load profiles.

Figure 7.4 presents the same simulation results as seen in Figure 7.3, but now also the increased number of households is taken into consideration. In 1990 there were approximately 2 million households and in 2050 the estimate for households is approximately 3.5 million. As can be seen, this changes the situation and the conclusions are not as clear as they were in the previous case; the increase in the number of households cancels out the effect of energy efficiency. Figure 7.3 better describes the situation of a city district with no significant change in the number of households, whereas Figure 7.4 presents the situation in Finland overall, or in growing areas.

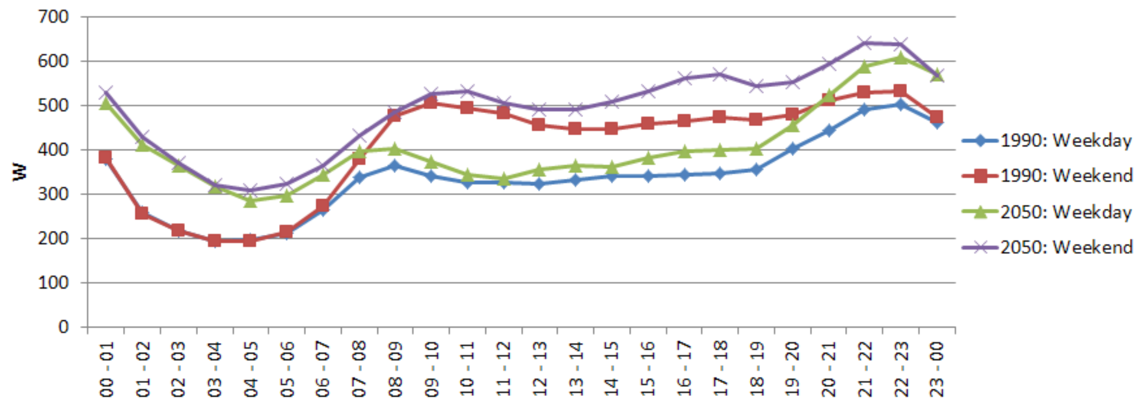


Figure 7.4: Daily load profiles - corrected with the amount of households.

Figure 7.5 presents the weekly load profiles for the scenarios S1 and S2 presented in in Chapter 5.

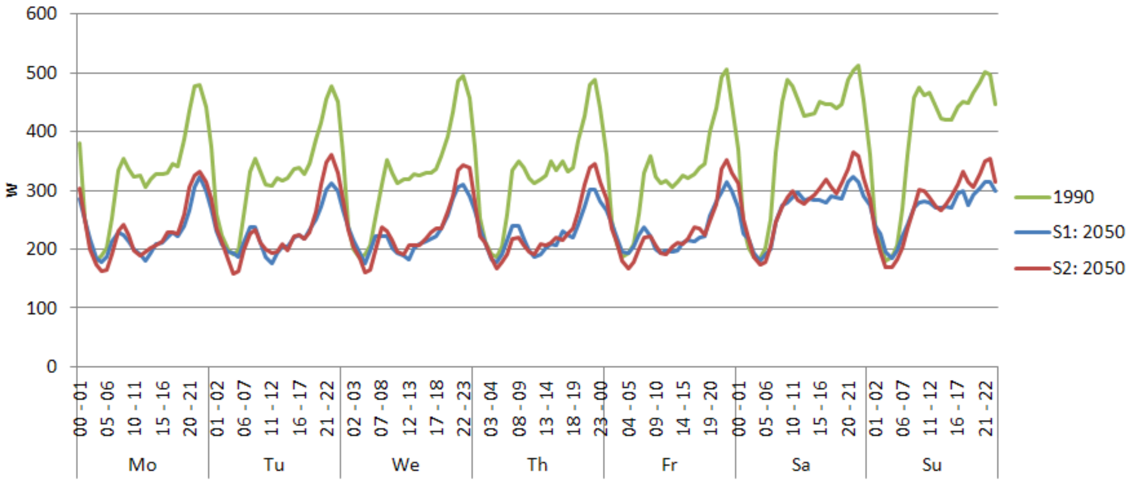
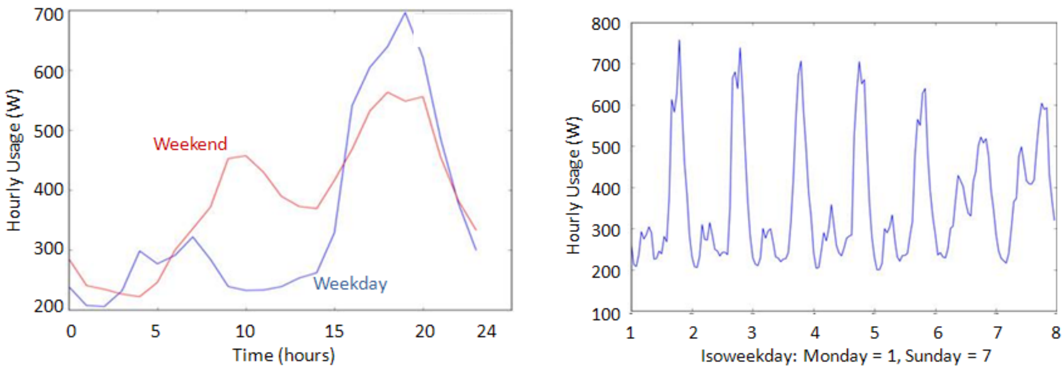


Figure 7.5: Weekly load profiles. Monday - Sunday.

For comparison, Figure 7.6 presents load profiles derived from the AMR-data. As can be observed, the shape of the profiles is similar to the simulated ones; however a careful comparison is not meaninful, because the short-term model is not calibrated yet. The most significant difference between the AMR-data and the simulation results is the weekend consumption, which given by the model is significantly higher than the AMR-data suggests.



(a) 2010 AMR day

(b) 2010 AMR week

Figure 7.6: Measured daily and weekly load profiles from AMR-data.

It seems that the current trends in household appliances are resulting in flatter load profiles even without special attempts, such as the demand response. However, the simulated load profiles are not taking into considerationall important factors, such as electric heating and HEVs.

7.4 Future Research

The model integration works well although the short-term model is not yet fully functional, and therefore limiting the use of the integrated model.

The integration could be done to work both ways. Now data is transferred only from the long-term model to the short-term model. The possibility to transfer data from the short-term model to the long-term model would enable many interesting phenomena, for instance the effect of load profile changes to the electricity production could be studied. In this case it would make sense to include the supply side submodel again in the long-term model, because flattening load profiles affect the hourly electricity price and therefore also the production methods. Flattening load profiles would result in lower demand for load following power plants. On the contrary, more volatile load profiles, e.g. due to lack of load control and load shifting activities, would result in higher demand for load following power plants instead of base power plants. The bidirectional integration is possible to implement with the Simantics platform [72].

Chapter 8

Discussion and Conclusion

This chapter states the conclusion and summarises what is done in this thesis. Also the scientific contribution to the field of electricity market research is discussed.

Section 8.1 presents the summary and conclusion. Section 8.2 states the scientific contribution of this thesis. Section 8.3 discusses the future research needed to be done.

8.1 Summary and Conclusion

The objective was to create a model able to simulate the change of household load profiles. The used method was a combination of system dynamics and a bottom-up modeling method.

The long-term model is capable of reproducing the scenarios found in the literature, and by changing the assumptions new scenarios can be generated. The power of the model lies in the feedback loops, nonlinearities, and delays, which are difficult to understand for human brains and affect the system behavior significantly in the long run.

The short-term model is capable of producing household load profiles; however, it is not yet calibrated to reproduce the current measured load profiles, and therefore more research is required. Nevertheless, the model is a structural bottom-up model, and by adjusting assumptions it can be used for load profile testing.

The integrated model combines long-term and short-term models. Using this entity it is possible to simulate the long-term change in load profiles. This is an important result since it helps understand the reasons behind the change and test different assumptions. For instance, if it is desired to flatten the load profiles, the effect of different policies can be tested.

The model can also be used to evaluate how different changes affect the behavior. Residential customers do not see the overall benefits as the electricity market utilities see them, and therefore incentives are needed to control household behavior. Finding the best way to control household behavior is not trivial. The model can be used to evaluate different strategies and help finding variables, which have the largest impact in the long run.

The simulation results suggest that the appliance electricity consumption is going to increase and the dwelling heating electricity consumption is going to decrease. The load profiles are likely to flatten, mostly because of the propagation of energy saving lighting technologies. However, the results are preliminary, and therefore they should be analysed with caution.

8.2 Scientific Contribution

The developed model is a new approach to load profile modeling. The preliminary results and expert evaluations suggest that the approach is useful and it can be used to better understand how load profiles are composed and how decision makers can influence them.

The model can also be used to evaluate the potential and likely propagation time of demand response methods, since the effect and the adoption time of different methods can be studied using simulations. This is an important aspect when talking about business models concerning the smart grid.

If electricity consumption trends are linked to load profiles in a practical way, it should be easier to anticipate how different policies are affecting electricity markets and household electricity consumption.

8.3 Future Research

Future research has already been discussed at the end of most of the chapters. Here a summary of these future research topics is made.

The model could be enhanced by adding a possibility to introduce new technology to the long-term model, which enables load shifting. The spreading of new technology appliances is a dynamic process and the usage time of the old appliances has to be taken into account to obtain a general view of the situation. The load shifting could be taken into account in the short-term model by introducing a controller which is capable of deciding what time of the day to consume electricity depending on the electricity price, outside temperature, etc.

Now, the model concentrates only on households, however, the model could be developed also to include companies, e.g. offices, shopping centres, and restaurants. Otherwise the model is not able to represent a whole city, or even a city district.

The modeling platform is also suitable for testing different tariff structures; the short-term model can be developed to take into account the effect of different tariffs, such as the effect of real-time pricing (RTP) on load profiles in the long-term. This can be used to answer questions like how many households need to adopt RTP-pricing to gain the desired load profile.

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Appendix A

Validation Results

Validation simulations are presented in this appendix. Some of the results are already presented in Section 5.4.

Validation Simulations against History Data

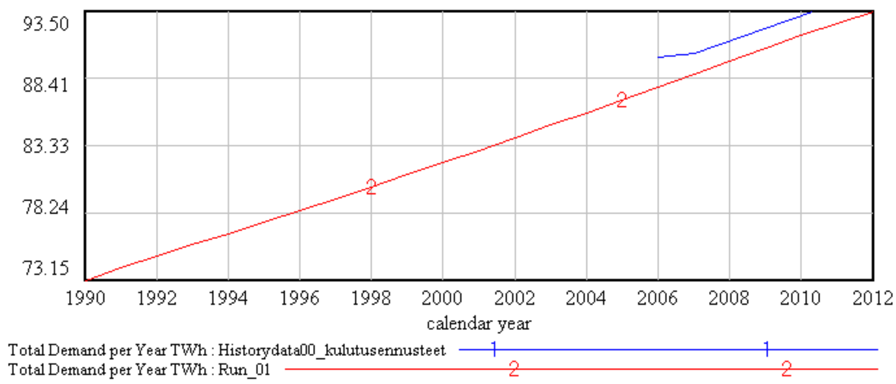


Figure A.1: Validation results: Total electricity consumption.

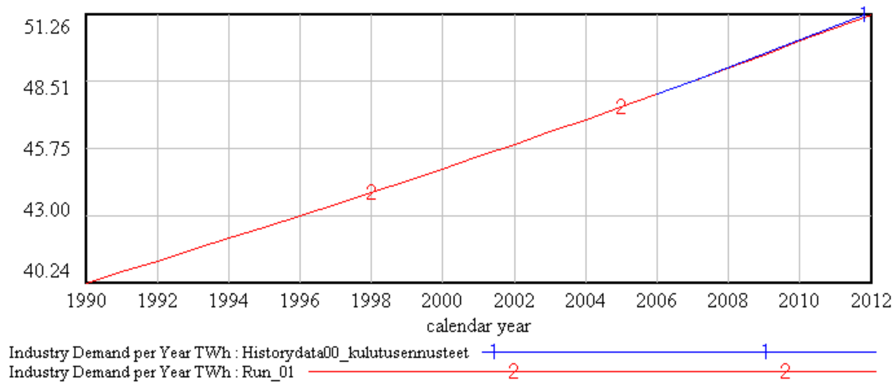


Figure A.2: Validation results: Industrial electricity consumption.

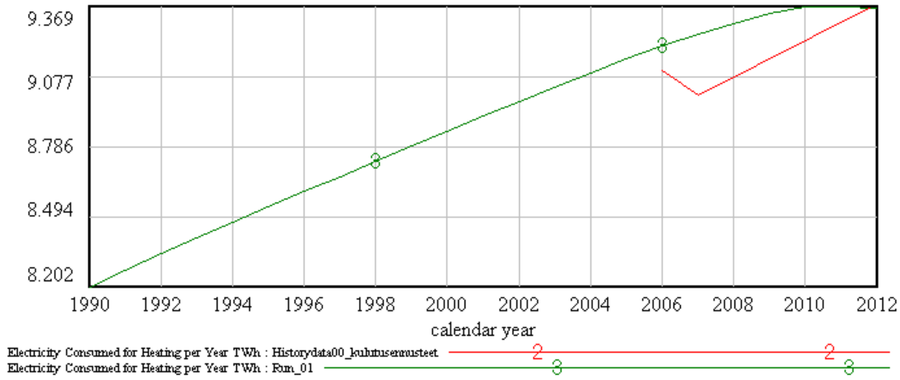


Figure A.3: Validation results: Dwelling stock electricity consumption.

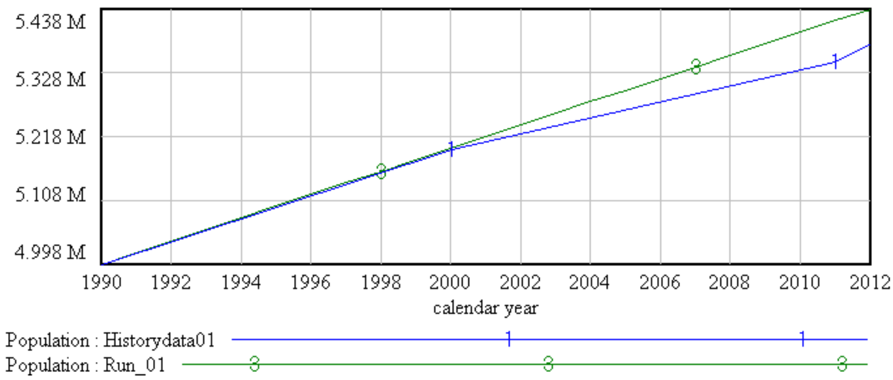


Figure A.4: Validation results: Population.

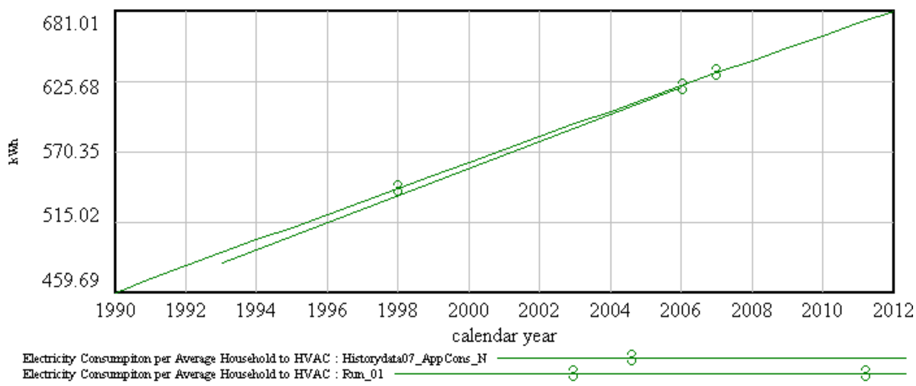


Figure A.5: Validation results: HVAC electricity consumption.

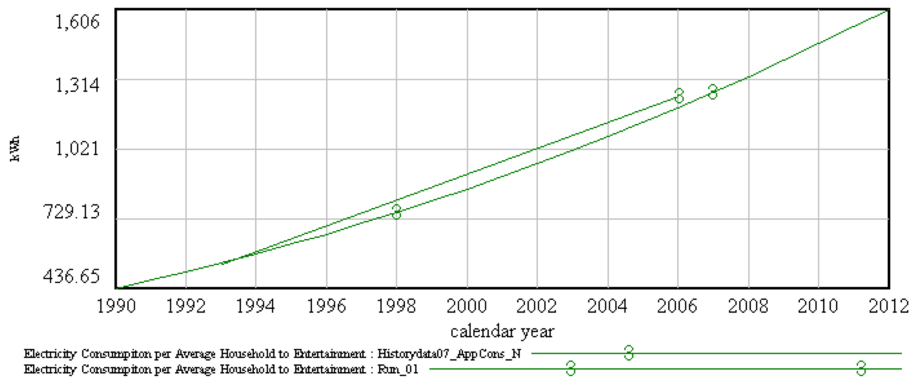


Figure A.6: Validation results: Entertainment electricity consumption.

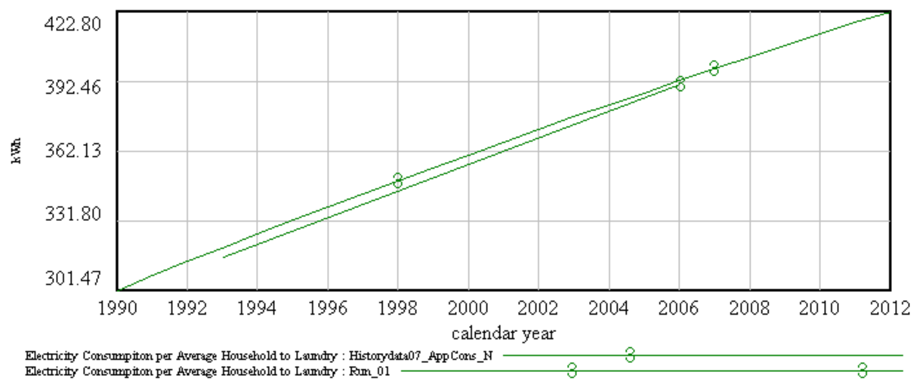


Figure A.7: Validation results: Laundry electricity consumption.

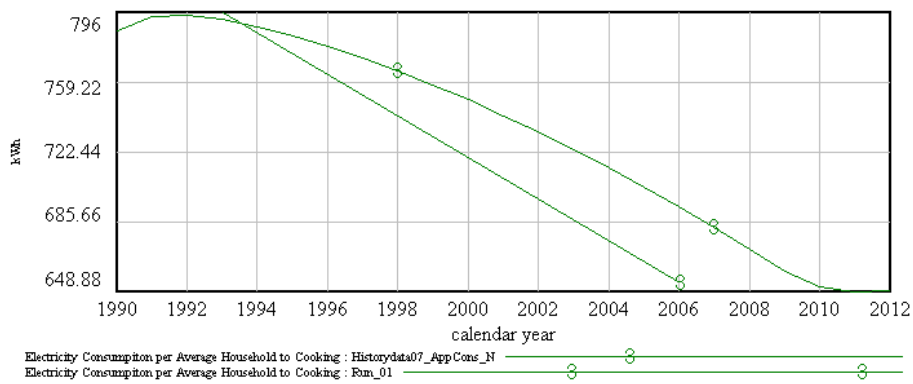


Figure A.8: Validation results: Cooking electricity consumption.

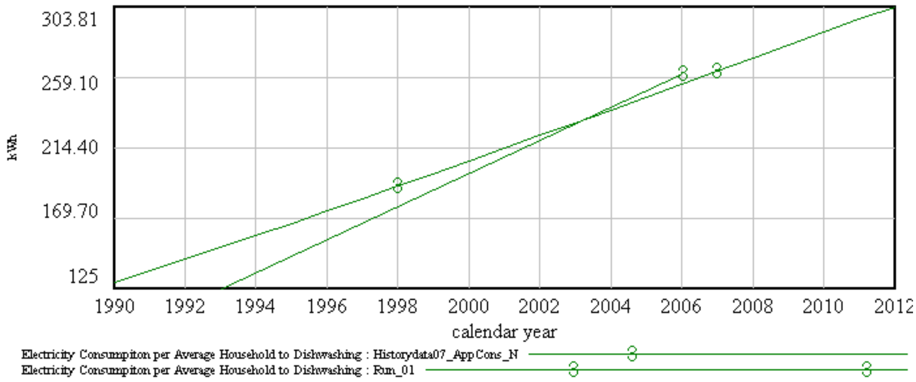


Figure A.9: Validation results: Dishwashing electricity consumption.

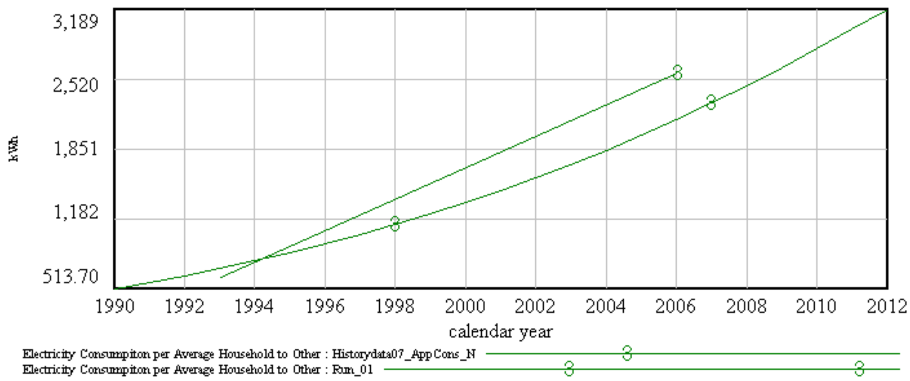


Figure A.10: Validation results: Other electricity consumption.

Appendix B

Long-term Model Details

Model equations are presented in this appendix. Some of the submodels are already presented in Section 5.3. For the readability of the equations some details are excluded, e.g. if-then-else(), max(), and min() structures. These structures are in the equations usually for the physical limitations, e.g. electricity consumption can not be negative. Also subscripts are neglected for the sake of readability.

The submodels are presented in the following order:

- Appliance Stock
- Dwelling Stock
- Electricity Price and Value
- Supply
- Hybrid and Electric Vehicles
- Money Spent to Electricity per Household
- Desire to Conserve Electricity
- Population
- Industry and Service Sector Demand
- Smart Meter Propagation

Subscripts used in the model:

- Household Devices: Lighting, car heating, sauna, HVAC, entertainment, laundry, cooking, refrigeration, floor heating, dishwashing, others
- Heating Method: Electric, district, oil, biomass, GSHP
- Building Type: Detached house, row house, apartments
- Electric Vehicles: EV, PHEV

Appliance Stock Submodel

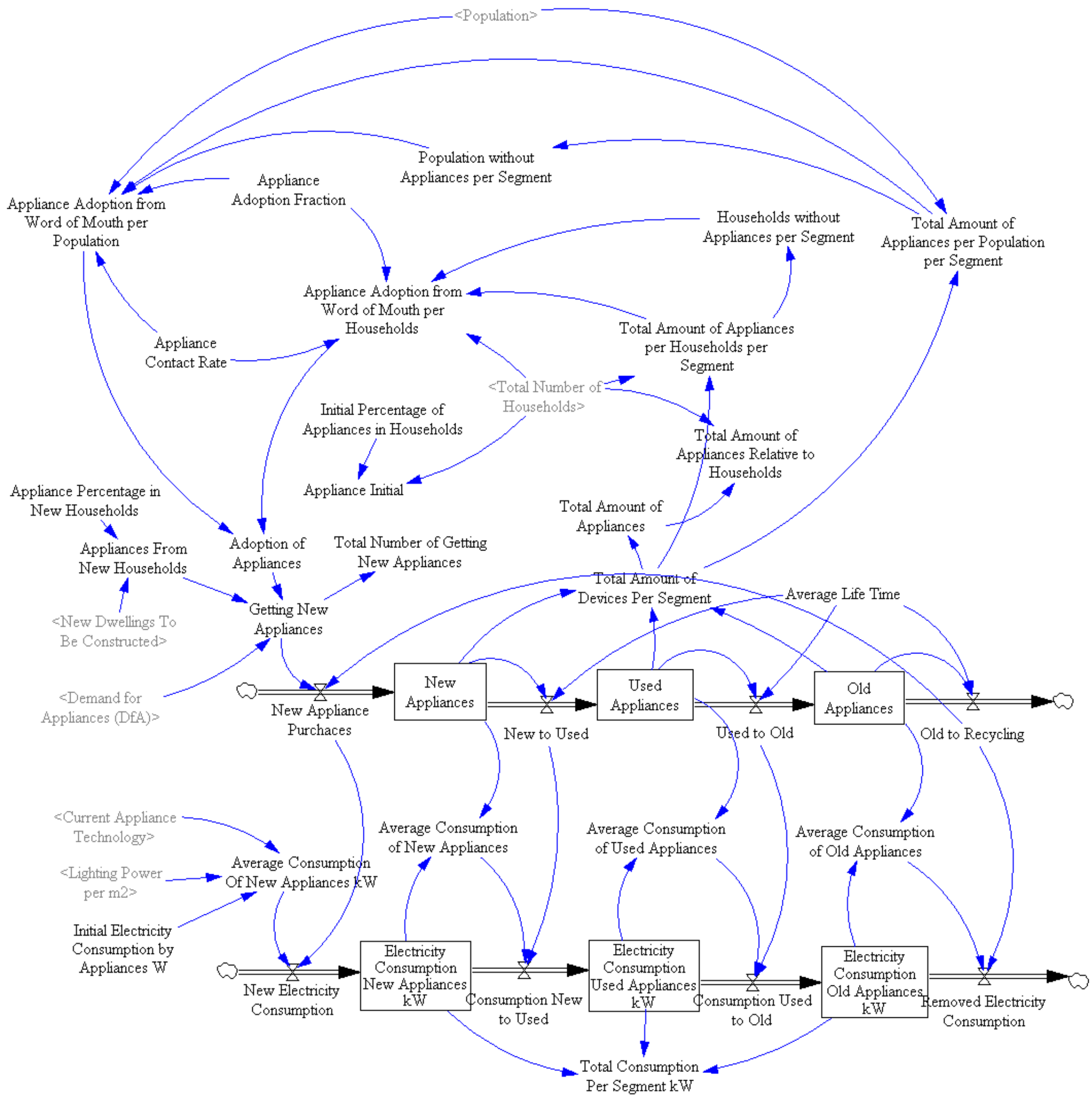


Figure B.1: Appliance stock submodel part 1.

Stocks

New Appliances = New Appliances Initial + $\int$ [New Appliance Purchace - New to Used]dt

Used Appliances = Used Appliances Initial + $\int$[New to Used - Used to Old]dt

Old Appliances = Old Appliances Initial + $\int$[Used to Old - Old to Recycling]dt

Electricity Consumption New Appliances kW = $\int$[New Electricity Consumption - Consumption New to Used]dt

Electricity Consumption Used Appliances kW = $\int$[Consumption New to Used - Consumption Used to Old]dt

Electricity Consumption Old Appliances kW = $\int$[Consumption Used to Old - Removed Electricity Consumption]dt

Flows

New Appliance Purchaces = Getting New Appliances + Old to Recycling
New to Used = New Appliances / Average Life Time
Used to Old = Used Appliances / Average Life Time
Old to Recycling = Old Appliances / Average Life Time
New Electricity Consumption = Average Consumption Of New Appliances kW × New Appliance Purchace
Consumption New to Used = New to Used × Average Consumption of New Appliances
Consumption Used to Old = Used to Old × Average Consumption of Used Appliances
Removed Electricity Consumption = Old to Recycling × Average Consumption of Old Appliances

Other

Average Consumption Of New Appliances kW = Initial Electricity Consumption by Appliances W / 1000 × Current Appliance Technology
Average Consumption of New Appliances = Electricity Consumption New Appliances kW / New Appliances
Average Consumption of Used Appliances = Electricity Consumption Used Appliances kW / Used Appliances
Average Consumption of Old Appliances = Electricity Consumption Old Appliances kW / Old Appliances
Total Consumption Per Average Household Per Segment kW = Electricity Consumption New Appliances kW + Electricity Consumption Old Appliances kW + Electricity Consumption Used Appliances kW
Appliances From New Households = New Dwellings To Be Constructed × Appliance Percentage in New Households
Getting New Appliances = Appliances From New Households + Adoption of Appliances
Adoption of Appliances = Appliance Adoption from Word of Mouth per Households
Total Number of Getting New Appliances = Getting New Appliances
Total Amount of Devices Per Segment = New Appliances + Old Appliances + Used Appliances
Total Amount of Appliances = Total Amount of Devices Per Segment
Appliance Adoption from Word of Mouth per Population = Population without Appliances per Segment × Total Amount of Appliances per Population per Segment × Population × Appliance Contact Rate × Appliance Adoption Fraction

Appliance Adoption from Word of Mouth per Households = Households without Appliances per Segment × Total Amount of Appliances per Households per Segment × Total Number of Houses × Appliance Contact Rate × Appliance Adoption Fraction
Population without Appliances per Segment = 1 - Total Amount of Appliances per Population per Segment
Appliance Initial = Total Number of Houses × Initial Percentage of Appliances in Households
Total Amount of Appliances per Households per Segment = Total Amount of Devices Per Segment / Total Number of Houses
Households without Appliances per Segment = 1 - Total Amount of Appliances per Households per Segment
Total Amount of Appliances per Population per Segment = Total Amount of Devices Per Segment / Population

Appliance Stock Submodel Calculations

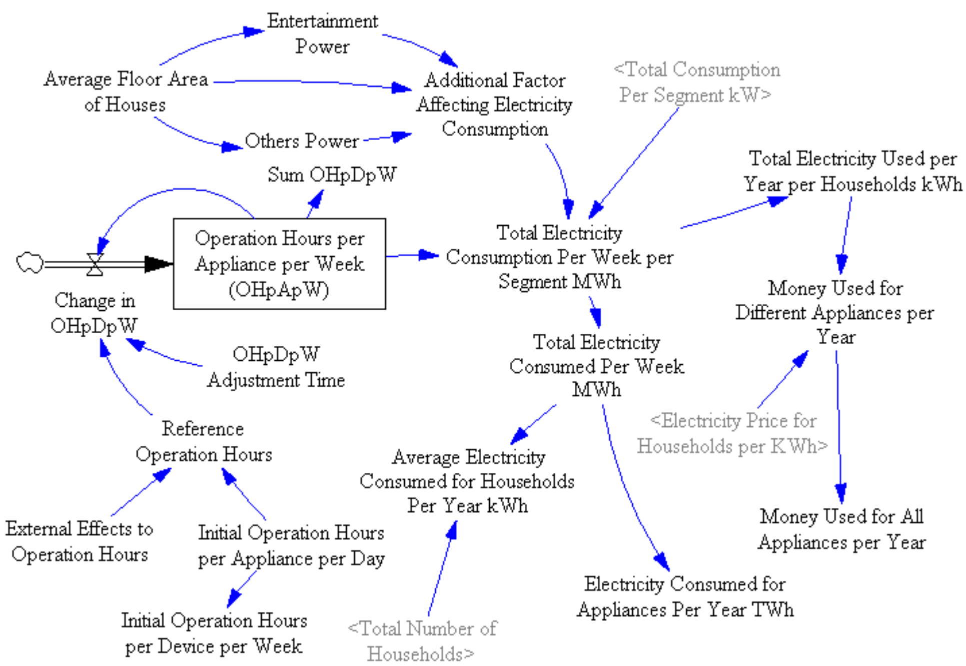


Figure B.2: Appliance stock submodel part 2.

Operation Hours per Appliance per Week (OHpApW) = $\int$[Change in OHpDpW]dt
Change in OHpDpW = (Reference Operation Hours - Operation Hours per Appliance per Week (OHpApW)) / OHpDpW Adjustment Time
Total Electricity Consumption Per Week per Segment MWh = Operation Hours per Appliance per Week (OHpApW) × Total Consumption Per Segment kW / 1000 × Additional Factor Affecting Electricity Consumption

Dwelling Stock Submodel

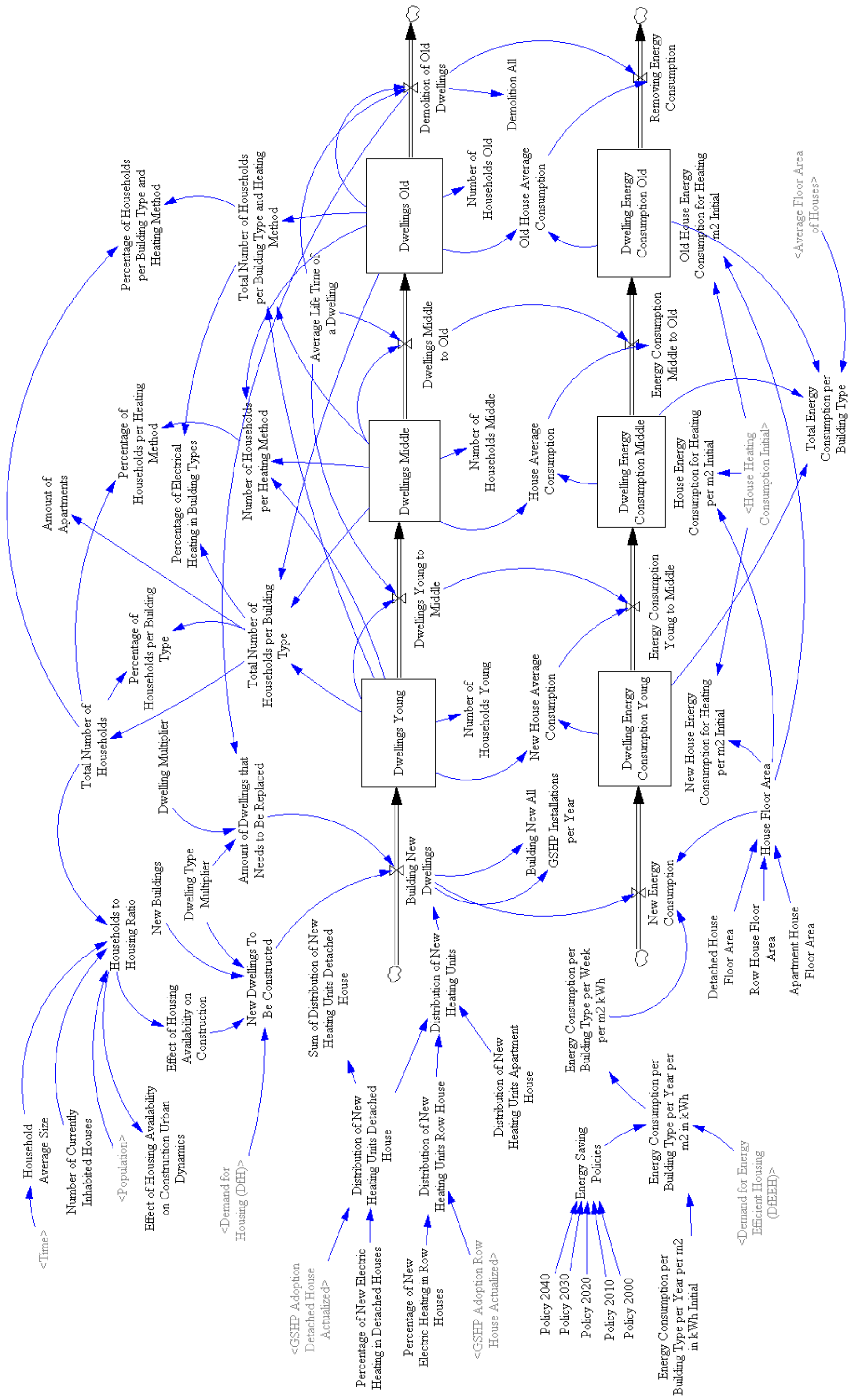


Figure B.3: Dwelling stock submodel.

Stocks

Dwellings Young = Number of Households per Building Type Young Initial+ $\int$[Building New Dwellings - Dwellings Young to Middle]dt
Dwellings Middle = Number of Households Middle Initial + $\int$[Dwellings Young to Middle - Dwellings Middle to Old]dt
Dwellings Old = Number of Households Old Initial + $\int$[Dwellings Middle to Old - Demolition of Old Dwellings]dt
Dwelling Energy Consumption Young = New House Energy Consumption for Heating per m2 Initial + $\int$[New Energy Consumption - Energy Consumption Young to Middle]dt
Dwelling Energy Consumption Middle = House Energy Consumption for Heating per m2 Initial + $\int$[Energy Consumption Young to Middle - Energy Consumption Middle to Old]dt
Dwelling Energy Consumption Old = Old House Energy Consumption for Heating m2 Initial + $\int$[Energy Consumption Middle to Old - Removing Energy Consumption]dt

Flows

Building New Dwellings = Distribution of New Heating Units × New Dwellings To Be Constructed + Distribution of New Heating Units × Amount of Dwellings that Needs to Be Replaced
Dwellings Young to Middle = Dwellings Young / Average Life Time of a Dwelling
Dwellings Middle to Old = Dwellings Middle / Average Life Time of a Dwelling
Demolition of Old Dwellings = Dwellings Old / Average Life Time of a Dwelling
New Energy Consumption = Building New Dwellings × Energy Consumption per Building Type per Week per m2
Energy Consumption Young to Middle = Dwellings Young to Middle × New House Average Consumption
Energy Consumption Middle to Old = House Average Consumption × Dwellings Middle to Old
Removing Energy Consumption = Old House Average Consumption × Demolition of Old Dwellings

Other

Total Number of Households per Building Type = Dwellings Middle + Dwellings Old + Dwellings Young
Number of Households per Heating Method = Dwellings Young + Dwellings Middle + Dwellings Old
Total Number of Households per Building Type and Heating Method = Dwellings Middle + Dwellings Old + Dwellings Young

Percentage of Households per Building Type and Heating Method = Total Number of Households per Building Type and Heating Method / Total Number of Houses
Percentage of Households per Heating Method = Number of Households per Heating Method / Total Number of Houses
Percentage of Households per Building Type = Total Number of Households per Building Type / Total Number of Houses
Total Number of Houses = (Total Number of Households per Building Type
Households to Housing Ratio = (Population / Household Average Size) / (Number of Currently Inhabited Houses × Total Number of Houses)
Effect of Housing Availability on Construction = Households to Housing Ratio
New Dwellings To Be Constructed = Effect of Housing Availability on Construction × New Buildings × Dwelling Type Multiplier
Amount of Dwellings that Needs to Be Replaced = Demolition of Old Dwellings × Dwelling Multiplier × Dwelling Type Multiplier
Distribution of New Heating Units Detached House = Percentage of New Electric Heating in Detached Houses - GSHP Adoption Detached House Actualized
Distribution of New Heating Units Row House = Percentage of New Electric Heating in Row Houses - GSHP Adoption Row House Actualized
Distribution of New Heating Units = Distribution of New Heating Units Detached House
Energy Consumption per Building Type per Year per m2 in kWh = Energy Consumption per Building Type per Year per m2 in kWh Initial × Energy Saving Policies / Demand for Energy Efficient Houses
Energy Consumption per Building Type per Week per m2 = Energy Consumption per Building Type per Year per m2 in kWh / 52
Total Energy Consumption per Building Type = Dwelling Energy Consumption Middle + Dwelling Energy Consumption Young + Dwelling Energy Consumption Old × House Floor Area
New House Average Consumption = Dwelling Energy Consumption Young / Dwellings Young
House Average Consumption = Dwelling Energy Consumption Middle / Dwellings Middle
Old House Average Consumption = Dwelling Energy Consumption Old / Dwellings Old

Dwelling Stock Submodel Calculations: Ground Source Heat Pump (GSHP) Propagation

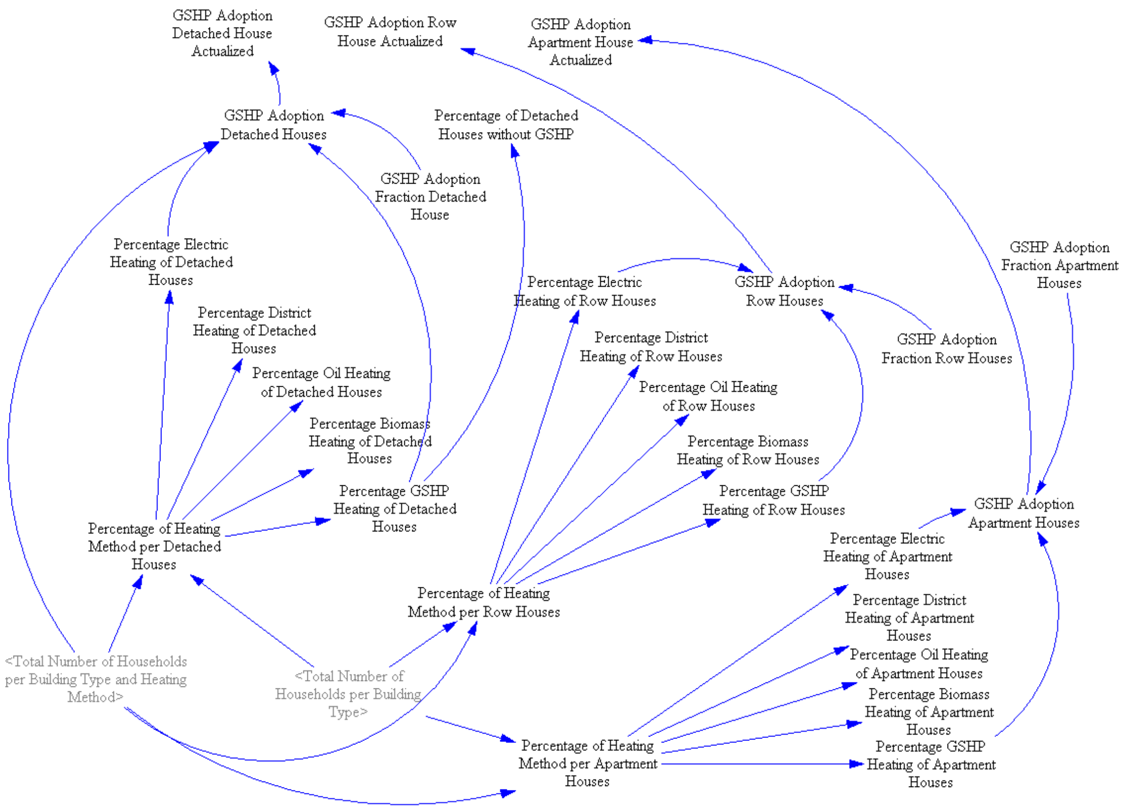
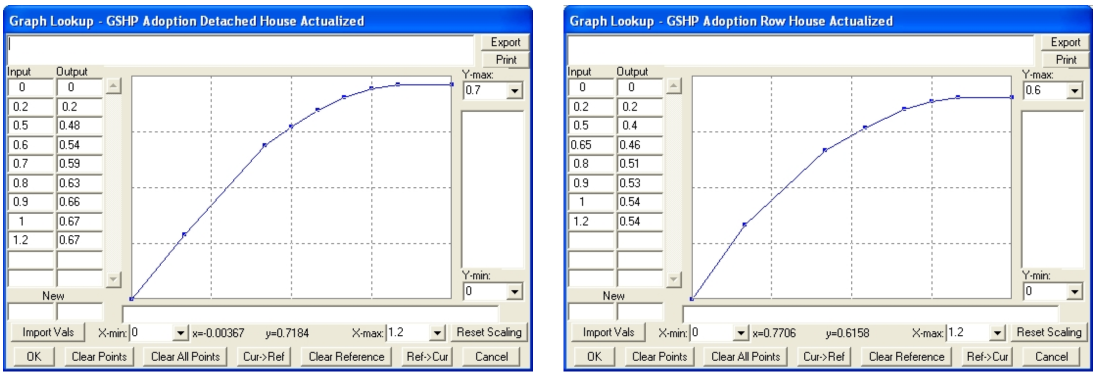


Figure B.4: Dwelling stock submodel calculations: Ground source heat pump (GSHP) propagation.

Percentage of Heating Method per Detached Houses = Total Number of Households per Building Type and Heating Method / Total Number of Households per Building Type
Percentage of Heating Method per Row Houses = Total Number of Households per Building Type and Heating Method / Total Number of Households per Building Type
Percentage of Heating Method per Apartment Houses = Total Number of Households per Building Type and Heating Method / Total Number of Households per Building Type
Percentage Electric Heating of Detached Houses = Percentage of Heating Method per Detached Houses
Percentage GSHP Heating of Detached Houses = Percentage of Heating Method per Detached Houses
Percentage Electric Heating of Row Houses = Percentage of Heating Method per Row Houses
Percentage GSHP Heating of Row Houses = Percentage of Heating Method per Row Houses

Percentage Electric Heating of Apartment Houses = Percentage of Heating Method per Apartment Houses
Percentage GSHP Heating of Apartment Houses = Percentage of Heating Method per Apartment Houses
GSHP Adoption Detached Houses = Percentage GSHP Heating of Detached Houses × Percentage Electric Heating of Detached Houses × GSHP Adoption Fraction Detached House
GSHP Adoption Row Houses = Percentage GSHP Heating of Row Houses × Percentage Electric Heating of Row Houses × GSHP Adoption Fraction Row Houses
GSHP Adoption Apartment Houses = Percentage GSHP Heating of Apartment Houses × Percentage Electric Heating of Apartment Houses × GSHP Adoption Fraction Apartment Houses
GSHP Adoption Detached House Actualized = LOOKUP(GSHP Adoption Detached Houses)
GSHP Adoption Row House Actualized = LOOKUP(GSHP Adoption Row Houses)



(a) GSHP Adoption Detached House Actualized LOOKUP

(b) GSHP Adoption Row House Actualized LOOKUP

Figure B.5: Lookup tables.

Dwelling stock submodel calculations: Initial values, Electriciy consumption, and demolished dwellings

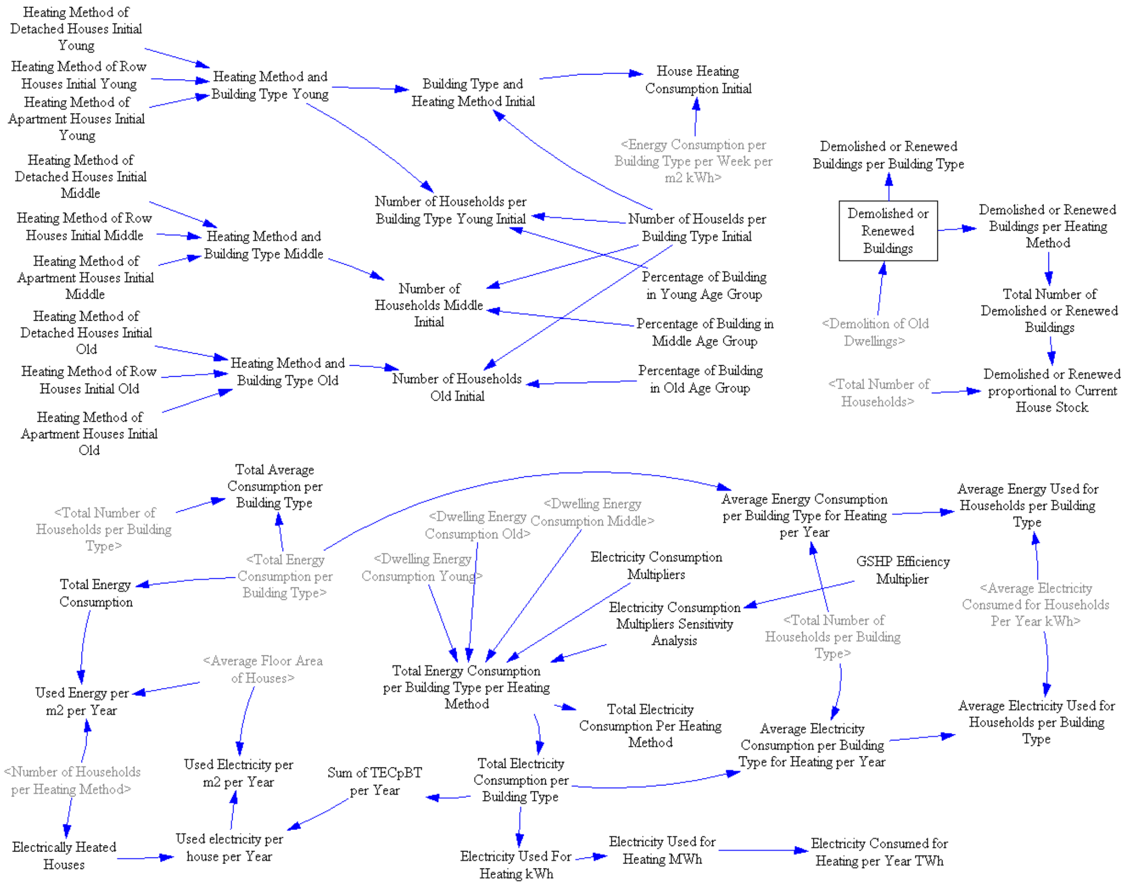


Figure B.6: Dwelling stock submodel calculations: Initial values, electriciy consumption, and demolished dwellings.

Building Type and Heating Method Initial = Heating Method and Building Type Young × Number of Houselds per Building Type Initial
Number of Households per Building Type Young Initial = Heating Method and Building Type Young × Number of Houselds per Building Type Initial × Percentage of Building in Young Age Group × 1.03
Number of Households Middle Initial = Heating Method and Building Type Middle × Number of Houselds per Building Type Initial × Percentage of Building in Middle Age Group × 1.03
Number of Households Old Initial = Heating Method and Building Type Old × Number of Houselds per Building Type Initial × Percentage of Building in Old Age Group × 1.04
House Heating Consumption Initial = Building Type and Heating Method Initial × Energy Consumption per Building Type per Week per m2

Total Energy Consumption per Building Type per Heating Method = ((Dwelling Energy Consumption Young + Dwelling Energy Consumption Middle + Dwelling Energy Consumption Old) × Electricity Consumption Multipliers × House Floor Area
Used Energy per m2 per Year = Total Energy Consumption / Average Floor Area of Houses / Number of Households per Heating Method × 52
Average Electricity Consumption per Building Type for Heating per Year = Total Electricity Consumption per Building Type / Total Number of Households per Building Type × 52
Average Energy Consumption per Building Type for Heating per Year = Total Energy Consumption per Building Type / Total Number of Households per Building Type × 52

Electricity Price and Value Submodel

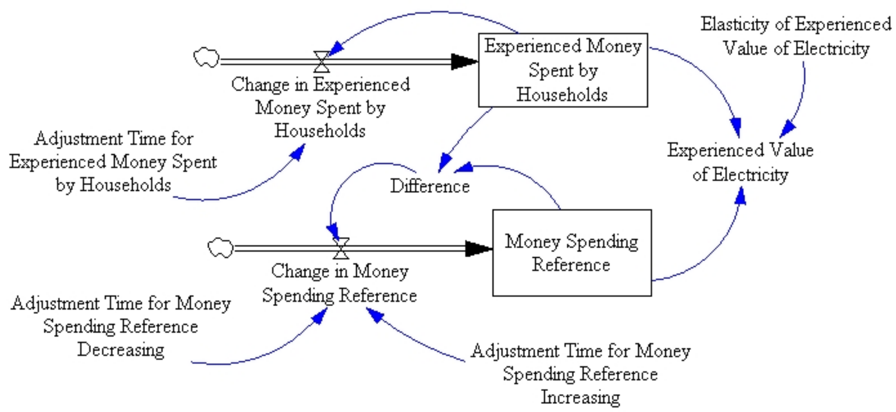


Figure B.7: Experienced value of electricity.

Stocks

Experienced Money Spent by Households = Money Spent to Electricity per Household + ∫[Change in Experienced Money Spent by Households]dt
Money Spending Reference = Money Spent to Electricity per Household + ∫[Change in Money Spending Reference]dt

Flows

Change in Experienced Money Spent by Households = (Money Spent to Electricity per Household-Experienced Money Spent by Households) / Adjustment Time for Experienced Money Spent by Households
Change in Money Spending Reference = IF THEN ELSE(Difference ¡ 0, Difference / Adjustment Time for Money Spending Reference Decreasing, Difference / Adjustment Time for Money Spending Reference Increasing)

Other

Difference = Experienced Money Spent by Households - Money Spending Reference

Experienced Value of Electricity = (Experienced Money Spent by Households / Money Spending Reference)$^{Elasticity of Experienced Value of Electricity}$

Supply Submodel

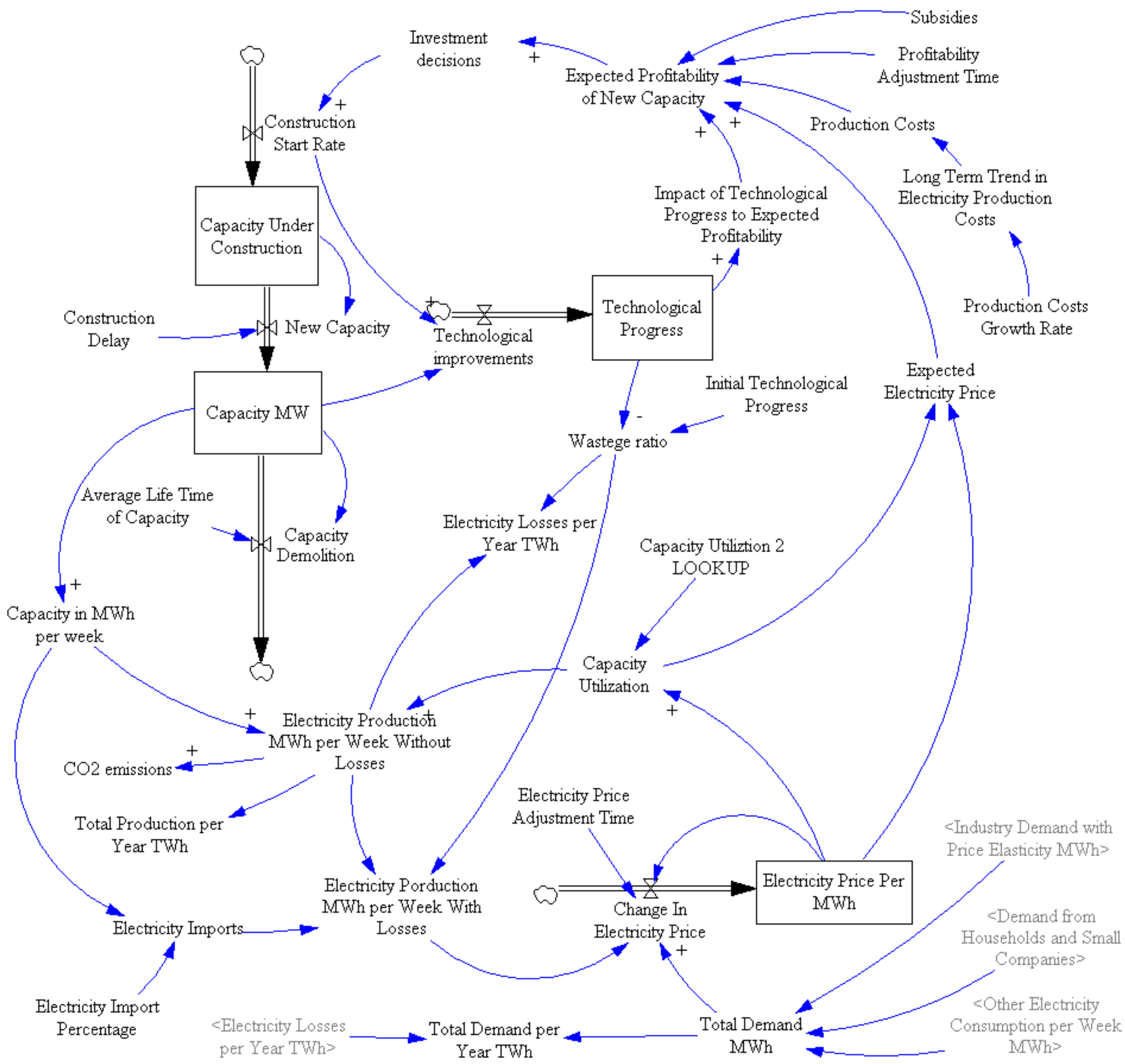


Figure B.8: Supply side submodel.

Hybrid and Electric Vehicle (HEV) Submodel

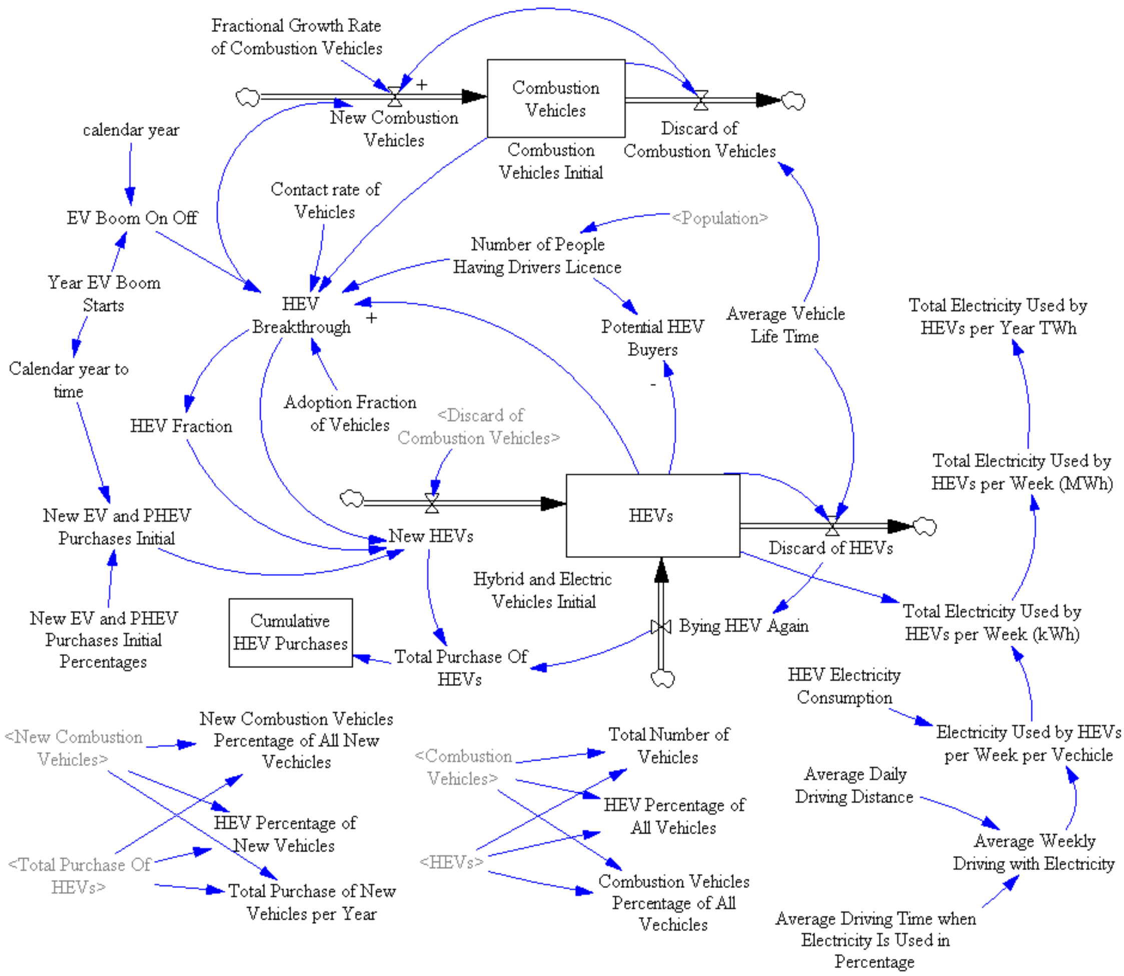


Figure B.9: Hybrid and electric vehicle (HEV) submodel.

Stocks

Combustion Vehicles = Combustion Vehicles Initial + $\int$[New Combustion Vehicles-Discard of Combustion Vehicles] dt
HEVs = $\int$ [Bying HEV Again+New HEVs-Discard of HEVs] dt
Cumulative HEV Purchases = $\int$[Total Purchase Of HEVs] dt

Flows

New Combustion Vehicles = Discard of Combustion Vehicles - HEV Breakthrough + Fractional Growth Rate of Combustion Vehicles
Discard of Combustion Vehicles = Combustion Vehicles / Average Vehicle Life Time

New HEVs = HEV Breakthrough + New EV and PHEV Purchases Initial
Discard of HEVs = HEVs / Average Vehicle Life Time
Bying HEV Again = Discard of HEVs

Other

HEV Breakthrough = HEVs[Electric Vehicles] × Combustion Vehicles/Number of People Having Drivers Licence × Contact rate of Vehicles × Adoption Fraction of Vehicles × EV Boom On Off
HEV Fraction = HEV Breakthrough / HEV Breakthrough
Average Weekly Driving with Electricity = 7 × Average Daily Driving Distance × Average Driving Time when Electricity Is Used in Percentage
Electricity Used by HEVs per Week per Vehicle = Average Weekly Driving with Electricity × HEV Electricity Consumption
Total Electricity Used by HEVs per Week (kWh) = Electricity Used by HEVs per Week per Vehicle × HEVs

Money Spent to Electricity per Households Submodel

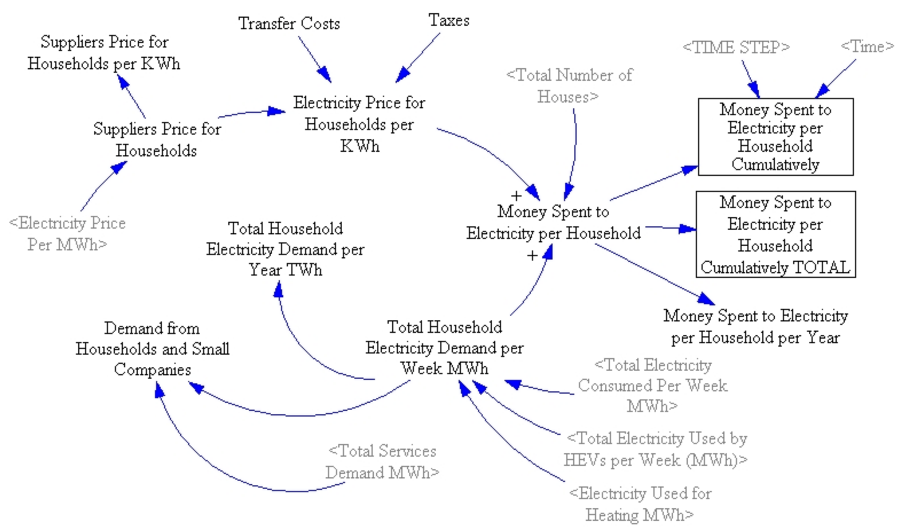


Figure B.10: Money spent to electricity per household submodel.

Suppliers Price for Households = SMOOTH3(Electricity Price Per MWh, 156)
Electricity Price for Households per KWh = Suppliers Price for Households / 1000 + Transfer Costs + Taxes
Money Spent to Electricity per Household = Electricity Price for Households per KWh × 1000 × Total Household Electricity Demand per Week MWh / Total Number of Houses

Total Household Electricity Demand per Week MWh = Electricity Used for Heating MWh + Total Electricity Consumed Per Week MWh + Total Electricity Used by HEVs per Week (MWh)
Total Household Electricity Demand per Year TWh = Total Household Electricity Demand per Week MWh / 1000 / 1000 × 52
Demand from Households and Small Companies = Total Services Demand MWh + Total Household Electricity Demand per Week MWh
Money Spent to Electricity per Household per Year = Money Spent to Electricity per Household × 52
Money Spent to Electricity per Household Cumulatively TOTAL = $\int$ [Money Spent to Electricity per Household] dt

Desire to Conserve Electricity Submodel

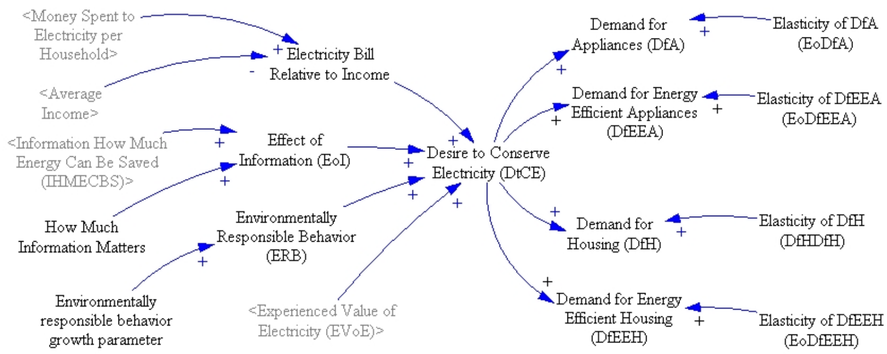


Figure B.11: Behavior submodel.

Electricity Bill Relative to Income = Money Spent to Electricity per Household / Average Income
Effect of Information (EoI) = 1-How Much Information Matters × Share of Population with AMR information
Environmentally Responsible Behavior (ERB) = 1 + RAMP(Environmentally responsible behavior growth parameter, 0 , 4000)
Desire to Conserve Electricity (DtCE) = (Environmentally Responsible Behavior (ERB) × Experienced Value of Electricity × Effect of Information (EoI) × Electricity Bill Relative to Income)
Demand for Appliances (DfA) = Desire to Conserve Electricity (DtCE) $^{ElasticityofDfA(EoDfA)}$
Demand for Energy Efficient Appliances (DfEEA) = Desire to Conserve Electricity (DtCE) $^{ElasticityofDfEEA(EoDfEEA)}$
Demand for Housing (DfH) = Desire to Conserve Electricity (DtCE) $^{ElasticityofDfH(DfHDfH)}$
Demand for Energy Efficient Housing (DfEEH) = Desire to Conserve Electricity (DtCE) $^{ElasticityofDfEEH(EoDfEEH)}$

Population Submodel

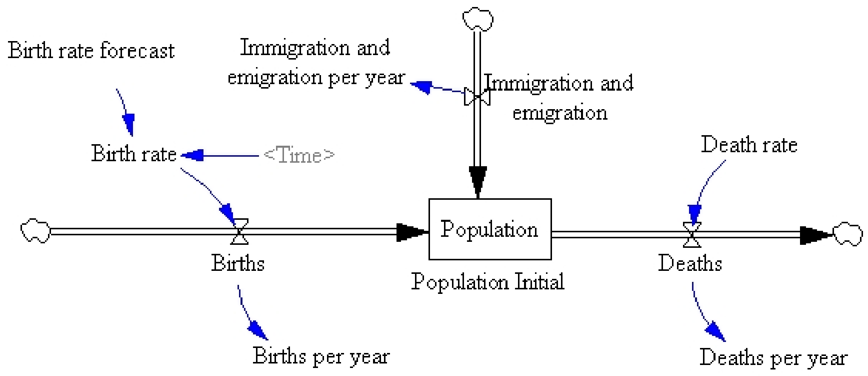


Figure B.12: Population submodel.

Stocks

Population = Population Initial + $\int$[Births - Deaths]dt

Flows

Births = Birth Rate
Deaths = Death Rate
Immigration and Emigration = 10000/52

Other

Births per Year = Births*52
Birth Rate = Birth rate forecast
Deaths per Year = Deaths*52
Immigration and Emigration per Year = Immigration and Emigration*52

Industry and Service Sector Demand Submodel

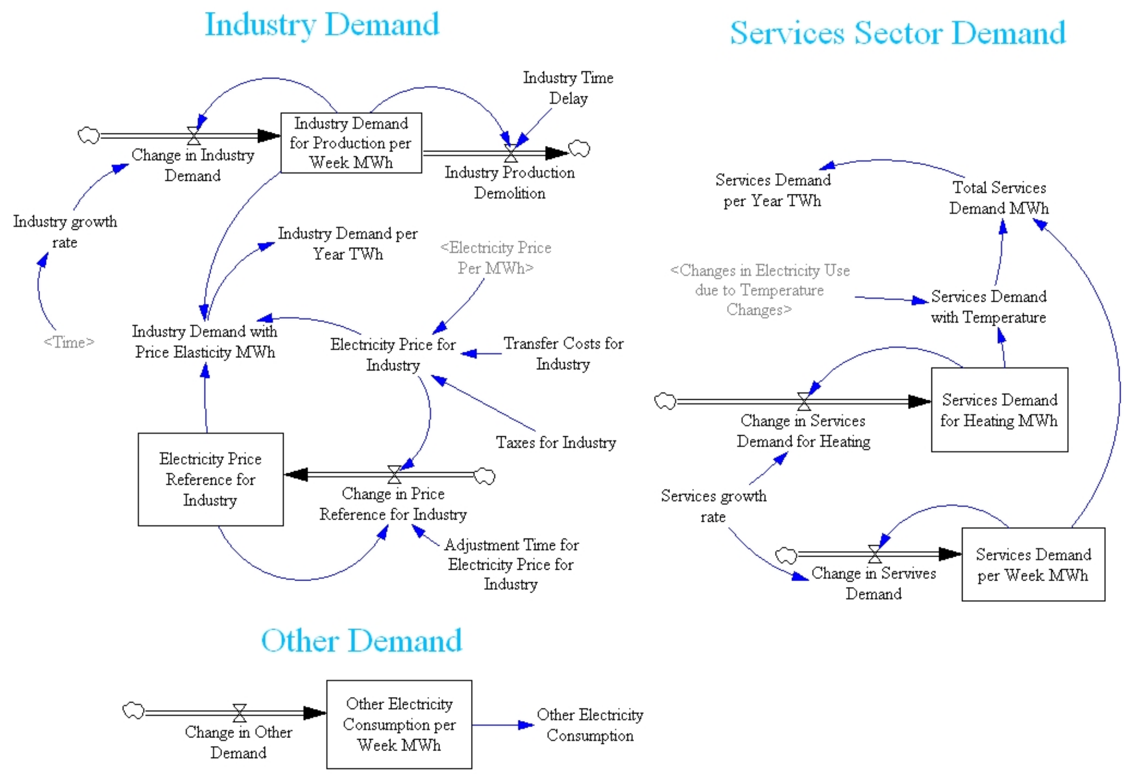


Figure B.13: Industry and service sector demand.

Stocks

Industry Demand per Week MWh = Industry Demand Initial + $\int$[Construction of Industry - Industry Production Demolition]dt
Electricity Price Reference for Industry = Electricity Price for Industry + $\int$[Change in Price Reference for Industry]dt
Services Demand for Heating MWh = Service Sector Demand for Heating Initial + $\int$[Change in Service Sector Demand for Heating]dt
Services Demand per Week MWh = Service Sector Demand Initial + $\int$[Change in Servive Sector Demand]dt
Other Electricity Consumption per Week MWh = Other Electricity Consumption Initial + $\int$[Change in Other Demand]dt

Flows

Construction of Industry = Industry growth rate $\times$ Industry Demand per Week MWh
Industry Production Demolition = Industry Demand per Week MWh / Industry Time Delay

Change in Price Reference for Industry = (Electricity Price for Industry - Electricity Price Reference for Industry) / Adjustment Time for Electricity Price for Industry
Change in Other Demand = Service Sector growth rate / Service Sector Demand for Heating MWh
Change in Service Sector Demand for Heating = Service Sector growth rate × Service Sector Demand per Week MWh
Change in Servive Sector Demand = 10

Other

Industry Demand with Price Elasticity MWh = Industry Demand per Week MWh + 0*(Electricity Price for Industry / Electricity Price Reference for Industry)$^{-0.1}$
Electricity Price for Industry = Electricity Price Per MWh + Taxes for Industry × Electricity Price Per MWh+Transfer Costs for Industry
Service Sector Demand with Temperature = Changes in Electricity Use due to Temperature Changes × Service Sector Demand for Heating MWh
Total Service Sector Demand MWh = Service Sector Demand with Temperature + Service Sector Demand per Week MWh

Smart Meter Propagation

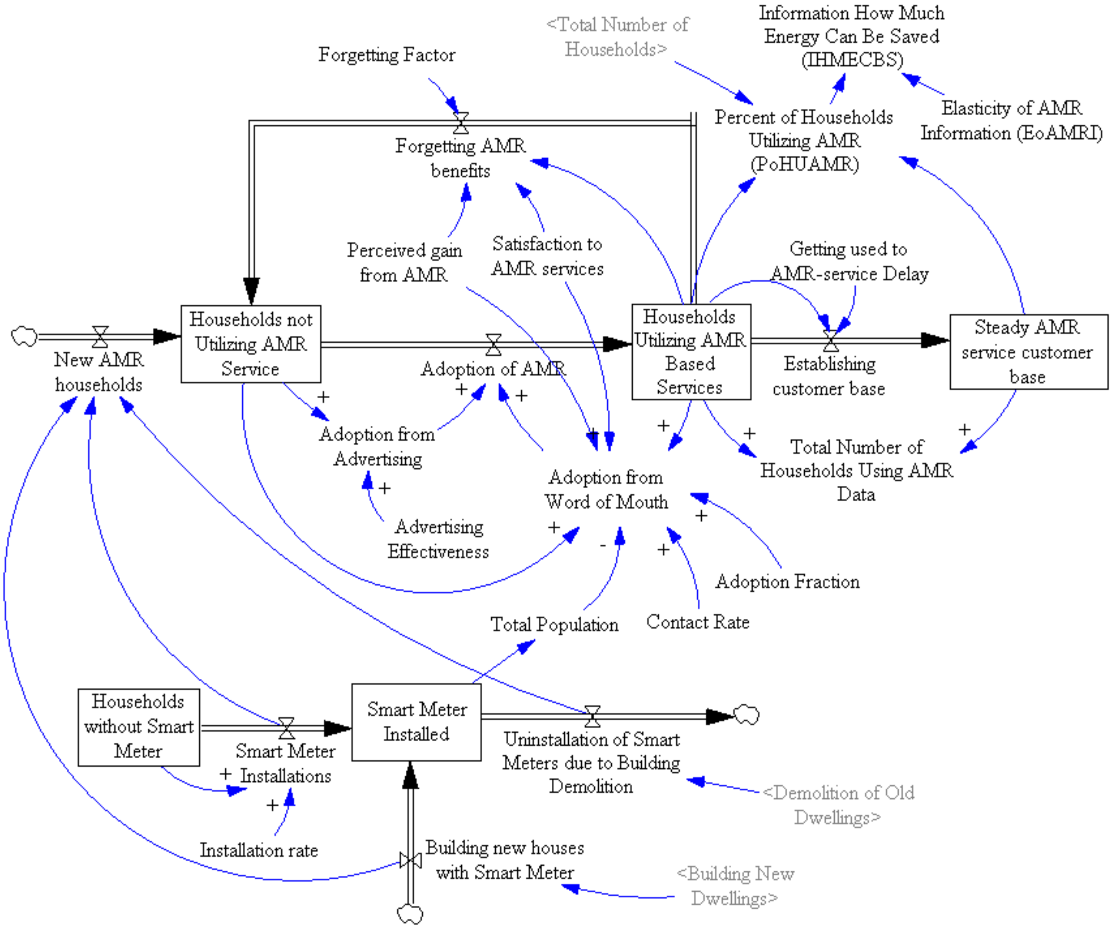


Figure B.14: Smart meter and AMR-service propagation.

Stocks

Households without Smart Meter = Households without Smart Meter Initial + $\int$[- Smart Meter Installations]dt
Smart Meter Installed = Smart Meter Installed Initial + $\int$[Smart Meter Installations + Building new houses with Smart Meter - Uninstallation of Smart Meters due to Building Demolition]dt
Households not Utilizing AMR Service = Households not Utilizing AMR Service Initial + $\int$[New AMR households - Adoption of AMR]dt
Households Utilizing AMR Based Services = Households Utilizing AMR Based Services Initial + $\int$[Adoption of AMR - Forgetting AMR benefits - Establishing customer base]dt
Steady AMR service customer base = Steady AMR service customer base Initial + $\int$[Establishing customer base]dt

Flows

Smart Meter Installations = Installation rate × Households without Smart Meter
Building new houses with Smart Meter = Building New Dwellings
Uninstallation of Smart Meters due to Building Demolition = Demolition of Old Dwellings
New AMR households = Smart Meter Installations + Building new houses with Smart Meter - Uninstallation of Smart Meters due to Building Demolition
Adoption of AMR = Adoption from Advertising + Adoption from Word of Mouth
Establishing customer base = Households Utilizing AMR Based Services / Getting used to AMR-service Delay
Forgetting AMR benefits = Households Utilizing AMR Based Services × Forgetting Factor+0*(1-Perceived gain from AMR)*(1-Satisfaction to AMR services)

Other

Adoption from Advertising = Advertising Effectiveness × Households not Utilizing AMR Service
Adoption from Word of Mouth = Households not Utilizing AMR Service × Households Utilizing AMR Based Services / Total Population × Contact Rate × Adoption Fraction + 0 × Perceived gain from AMR × Satisfaction to AMR services
Total Number of Households Using AMR Data = Households Utilizing AMR Based Services + Steady AMR service customer base
Percent of Households Utilizing AMR (PoHUAMR) = (Households Utilizing AMR Based Services + Steady AMR service customer base) / Total Number of Households
Information How Much Energy Can Be Saved (IHMECBS) = (1 + Percent of Households Utilizing AMR (PoHUAMR))$^{E}lasticityofAMRInformation(EoAMRI)$

Parameter Values

Table B.1: Add caption

	Initial Percentage of Appliances	**Initial electricity power by appliances (W)**	**Operation Hours per Appliance per Day (hours)**	**Average Life Time (years)**	**Technology Adoption Fraction**	**Appliance Adoption Fraction**
Lighting	1		2.4	2	0.7	0
Car Heating	0.3	800	1	15	0.01	0.01
Sauna	0.403	8000	0.2	15	0.01	0.05
HVAC	0.3	87	24	30	0.1	0.1
Entertainment	0.17	500	7	7	0.33	1.25
Laundry	0.765	700	1	12	0.1	1.02
Cooking	0.99	390	3	16	0.1	0
Refrigeration	0.52	390	24	13	0.65	0.1
Floor Heating	0.05	300	8	30	0.01	0
Dishwashing	0.314	800	0.7	12	0.2	1.05
Others	0.1	500	0.5	5	0.01	2

Appendix C

Short-term Model Details

Submodels are presented in the following order:

- Occupants
- Lighting
- Refregeration
- Car Heating
- Entertainment
- Sauna
- Floor Heating
- Cooking
- Dishwashing
- Laudry
- HVAC
- Others

Figure C.1 presents how the submodels are connected.

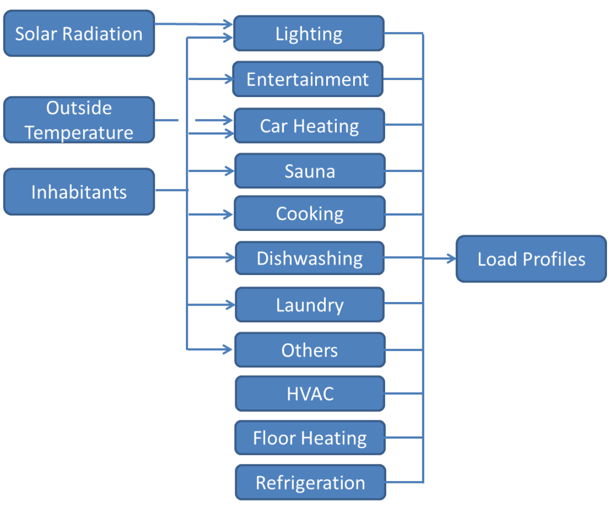


Figure C.1: The short-term model - model structure.

Inhabitants

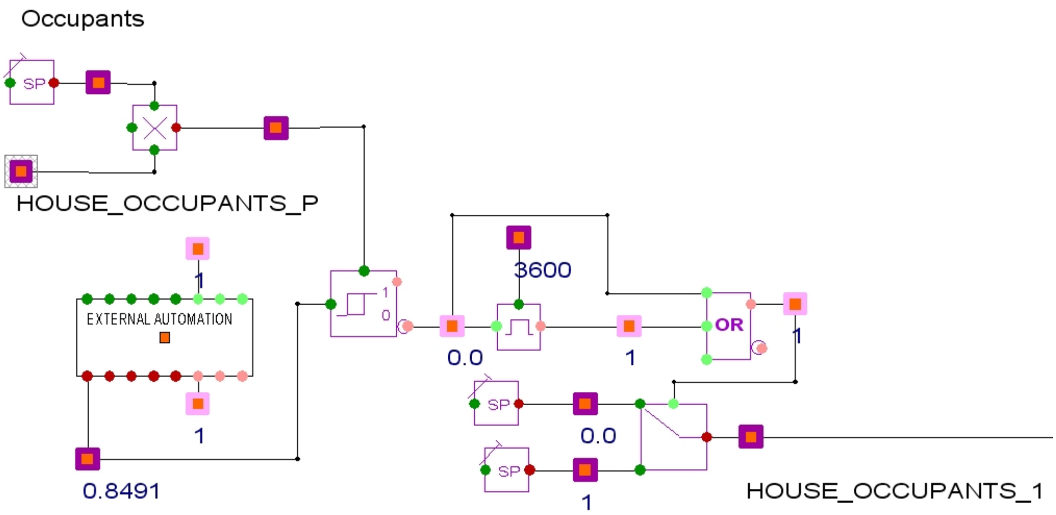


Figure C.2: Short-term model - occupants.

Lighting

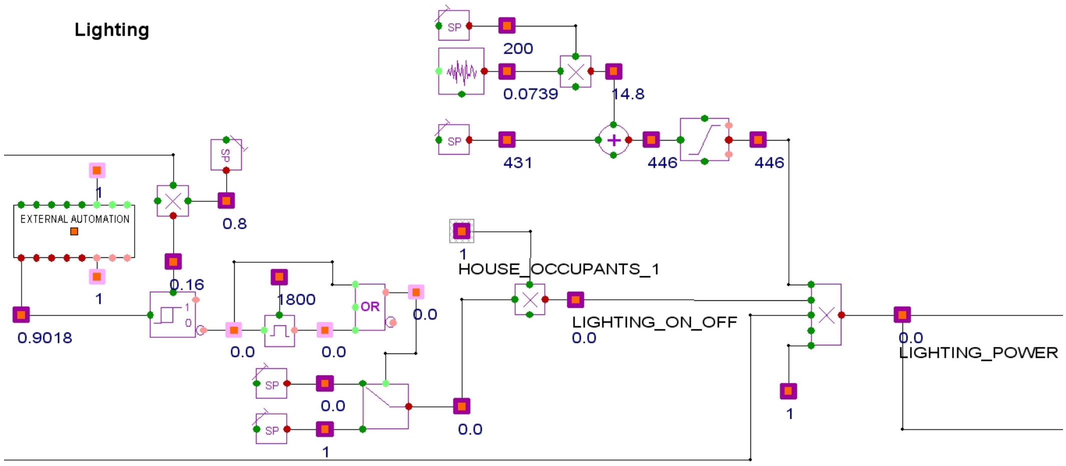


Figure C.3: Short-term model - lighting.

Refrigeration

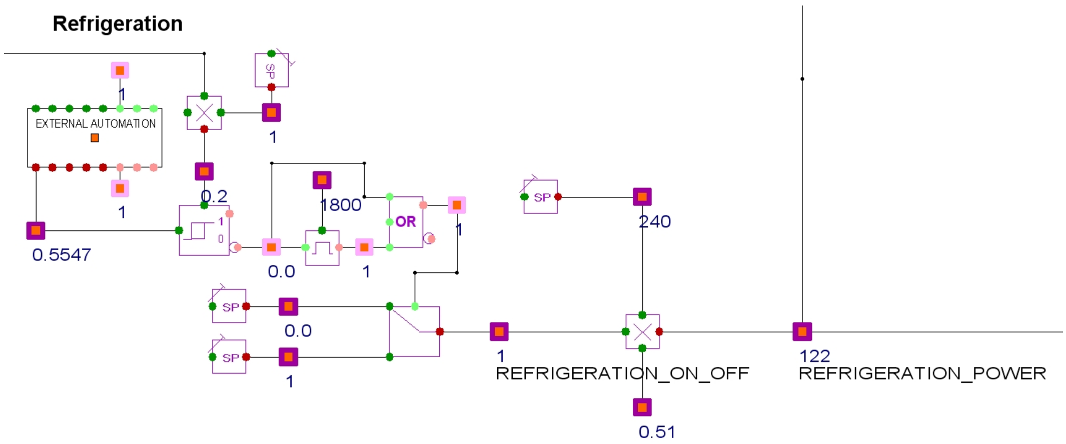


Figure C.4: Short-term model - refrigeration devices.

Car heating

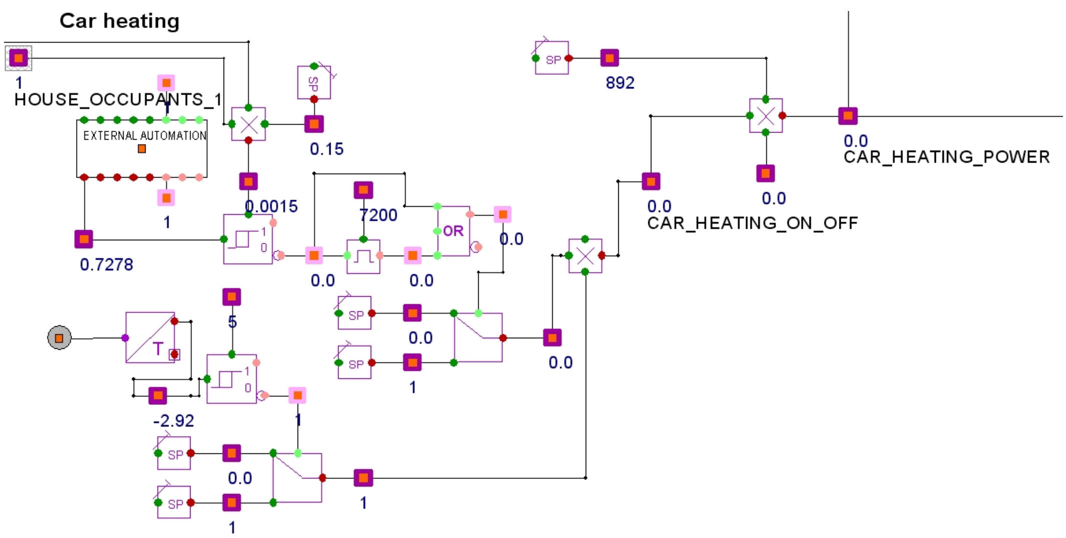


Figure C.5: Short-term model - car heating.

Entertainment

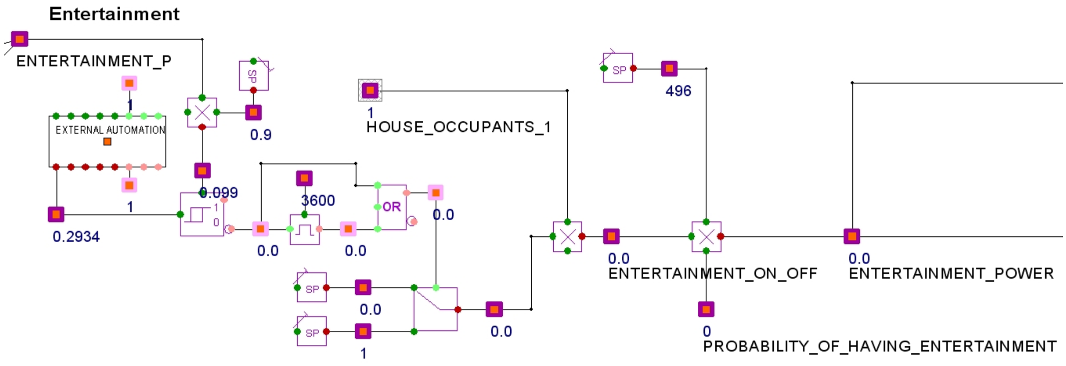


Figure C.6: Short-term model - entertainment.

Sauna

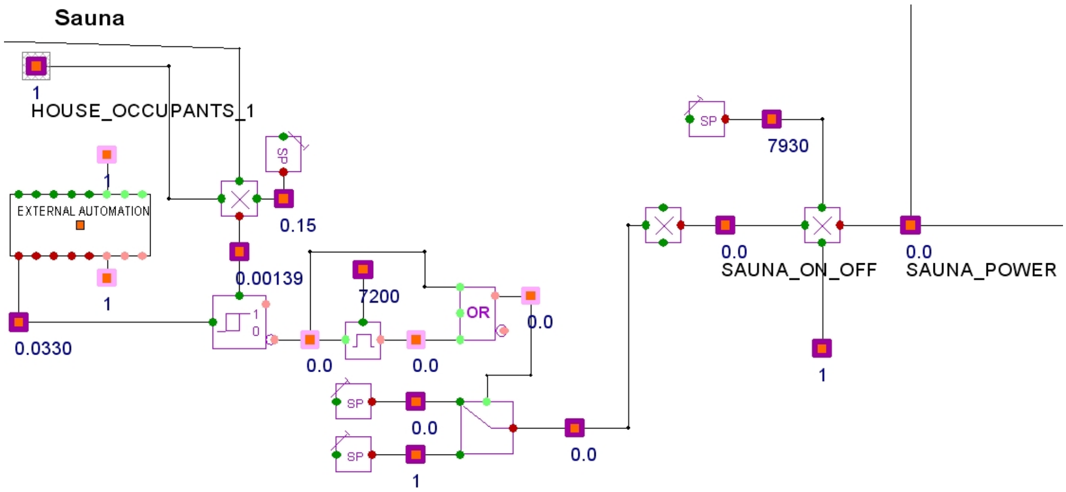


Figure C.7: Short-term model - sauna.

Floor Heating

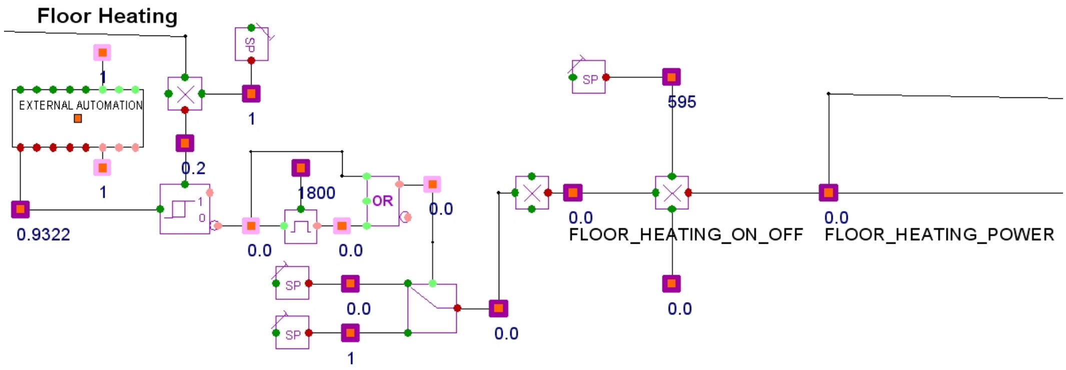


Figure C.8: Short-term model - floor heating.

Cooking

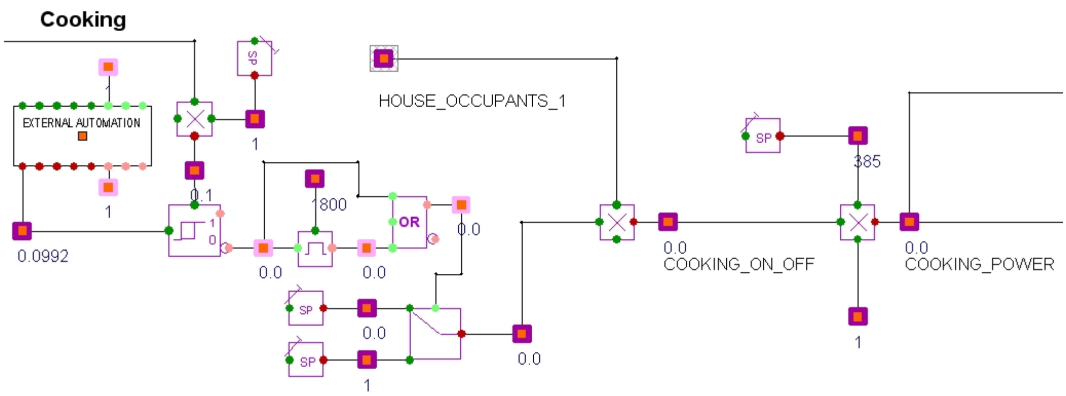


Figure C.9: Short-term model - cooking.

Dishwashing

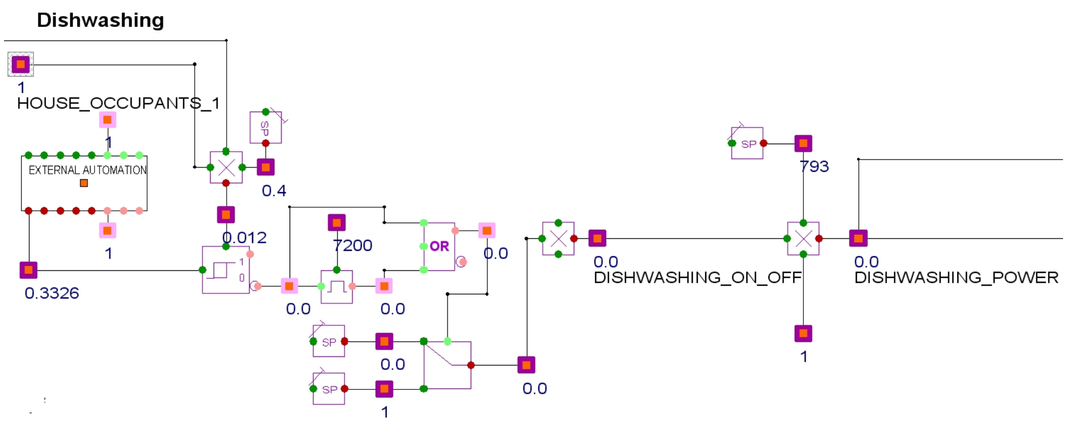


Figure C.10: Short-term model - dishwashing.

Laudry

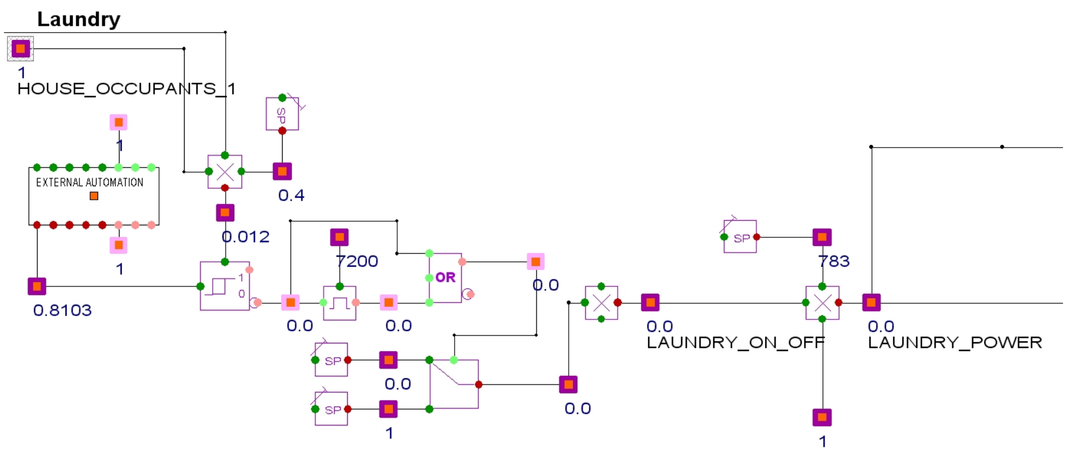


Figure C.11: Short-term model - laundry.

HVAC

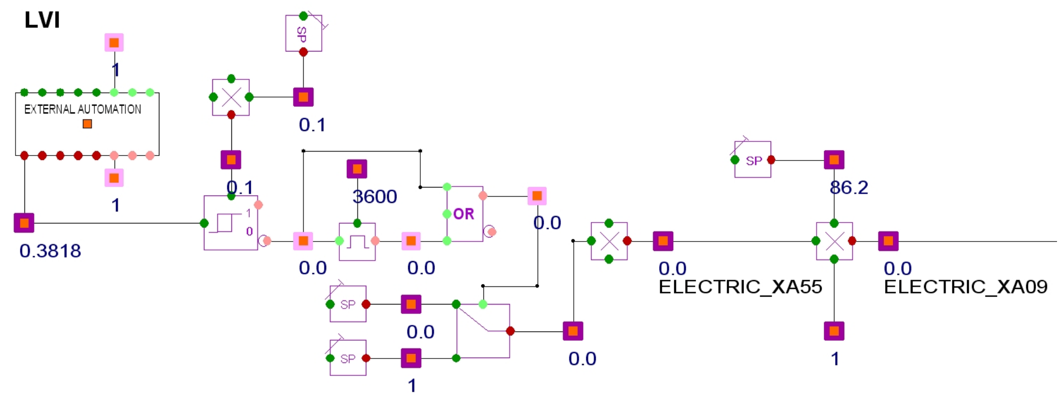


Figure C.12: Short-term model - HVAC.

Others

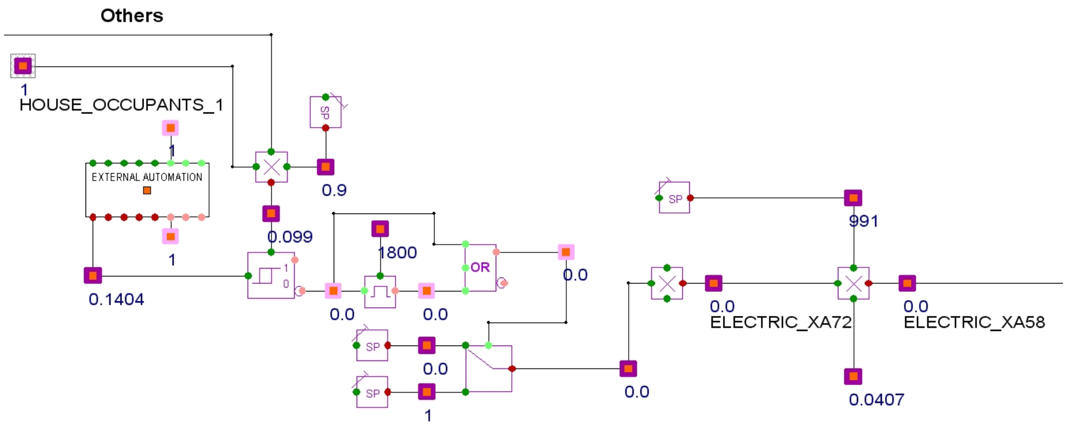


Figure C.13: Short-term model - others.

Probability Distributions

Table C.1: Probability distributions

At home		Lighting		Sauna		Car heating		Entertainment		Laundry		Refrigeration		Cooking		Floor heating		Dishwashing		LVI		Others	
Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
0.9	0.95	0.1	0.1	0.009	0.009	0.01	0.01	0.1	0.1	0.03	0.03	0.2	0.2	0.1	0.1	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.96	0.98	0.05	0.05	0.007	0.007	0.01	0.01	0.07	0.07	0.03	0.03	0.2	0.2	0.07	0.07	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.96	0.98	0.05	0.05	0.005	0.005	0.01	0.01	0.04	0.04	0.03	0.03	0.2	0.2	0.05	0.05	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.96	0.98	0.05	0.05	0.005	0.005	0.05	0.05	0.01	0.01	0.03	0.03	0.2	0.2	0.05	0.05	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.96	0.98	0.05	0.05	0.005	0.005	0.1	0.1	0.01	0.01	0.03	0.03	0.2	0.2	0.05	0.05	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.85	0.98	0.1	0.1	0.005	0.005	0.13	0.13	0.01	0.01	0.03	0.03	0.2	0.2	0.07	0.07	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.6	0.98	0.3	0.3	0.005	0.005	0.14	0.14	0.01	0.01	0.03	0.03	0.2	0.2	0.09	0.09	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.4	0.95	0.6	0.6	0.005	0.005	0.14	0.14	0.02	0.02	0.03	0.03	0.2	0.2	0.11	0.11	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.3	0.8	0.9	0.9	0.006	0.006	0.14	0.14	0.04	0.04	0.03	0.03	0.2	0.2	0.12	0.12	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.3	0.7	0.9	0.9	0.007	0.007	0.13	0.13	0.06	0.06	0.03	0.03	0.2	0.2	0.13	0.13	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.3	0.6	0.95	0.95	0.008	0.008	0.11	0.11	0.08	0.08	0.03	0.03	0.2	0.2	0.14	0.14	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.3	0.5	0.95	0.95	0.009	0.009	0.09	0.09	0.1	0.1	0.03	0.03	0.2	0.2	0.16	0.16	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.3	0.5	0.95	0.95	0.01	0.01	0.07	0.07	0.12	0.12	0.03	0.03	0.2	0.2	0.18	0.18	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.3	0.5	0.95	0.95	0.011	0.011	0.05	0.05	0.14	0.14	0.03	0.03	0.2	0.2	0.2	0.2	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.3	0.5	0.95	0.95	0.012	0.012	0.04	0.04	0.16	0.16	0.03	0.03	0.2	0.2	0.22	0.22	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.3	0.5	0.95	0.95	0.012	0.012	0.04	0.04	0.18	0.18	0.03	0.03	0.2	0.2	0.24	0.24	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.3	0.5	0.95	0.95	0.012	0.012	0.03	0.03	0.2	0.2	0.03	0.03	0.2	0.2	0.26	0.26	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.3	0.5	0.95	0.95	0.012	0.012	0.03	0.03	0.22	0.22	0.03	0.03	0.2	0.2	0.26	0.26	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.4	0.5	0.95	0.95	0.012	0.012	0.02	0.02	0.24	0.24	0.03	0.03	0.2	0.2	0.26	0.26	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.5	0.6	0.95	0.95	0.012	0.012	0.02	0.02	0.24	0.24	0.03	0.03	0.2	0.2	0.26	0.26	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.6	0.7	0.95	0.95	0.012	0.012	0.02	0.02	0.24	0.24	0.03	0.03	0.2	0.2	0.24	0.24	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.7	0.8	0.95	0.95	0.012	0.012	0.01	0.01	0.22	0.22	0.03	0.03	0.2	0.2	0.22	0.22	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.8	0.9	0.8	0.8	0.011	0.011	0.01	0.01	0.18	0.18	0.03	0.03	0.2	0.2	0.14	0.14	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03
0.9	0.95	0.5	0.5	0.01	0.01	0.01	0.01	0.14	0.14	0.03	0.03	0.2	0.2	0.1	0.1	0.2	0.2	0.03	0.03	0.03	0.03	0.03	0.03